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SPECIAL ISSUE: DYNAMIC RELATIONSHIPS IN TEAMS

Advancing Research on Team Process Dynamics:

Theoretical, Methodological, and Measurement Considerations

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SPECIAL ISSUE

DYNAMIC RELATIONSHIPS IN TEAMS

Abstract

Team processes are inherently dynamic phenomena theoretically, but they have largely been treated as static in research. It is well established that they are important contributors to team effectiveness; the lack of attention to dynamics means that *team process mechanisms* are essentially unstudied. I examine three primary themes. First, I speculate as to why it is that research treatments of team processes are largely static and what may account for this inertia. Second, I consider the conceptual underpinnings of process dynamics with respect to (a) emergence across levels and (b) in terms of variability, trajectory, and cyclical fluctuation. Third, I discuss three ways that research on team process dynamics can be advanced by: (1) adapting existing research methods, (2) creating innovative measurement techniques, and (3) advancing new research paradigms. Empirical examination of team dynamics is on the research frontier. These suggestions hold promise for advancing understanding of dynamic process mechanisms.

ADVANCING RESEARCH ON TEAM PROCESS DYNAMICS:

THEORETICAL, METHODOLOGICAL, AND MEASUREMENT CONSIDERATIONS

Researchers in social and organizational psychology have been studying team effectiveness and its underpinnings for over sixty years. Much of that research has been strongly influenced by McGrath's (1964) input – process – output (IPO) heuristic, which emphasizes the critical role of team processes as the mechanism by which individual team members combine their resources and capabilities, shaped by the context, to resolve team task demands (Kozlowski & Ilgen, 2006). Although the overall influence of the IPO heuristic has been positive, there have also been unintended consequences – one of which is the static treatment of team processes.

The dominant locus of research on team effectiveness migrated from social psychology to organizational psychology and behavior in the early 1990s, prompting Levine and Moreland (1990, p. 620) to conclude that, "Groups are alive and well, but living elsewhere ….The torch has been passed to (or, more accurately, picked up by) colleagues in other disciplines, particularly organizational psychology." This shift also marked an increased emphasis on the mediating role of team processes; such research exploded. This has been good for advancing knowledge, but advances often have unintended consequences. Although contemporary theory emphasizes feedback loops and recursive relationships as a critical adjunct to the IPO heuristic, and scholars have almost universally acknowledged that team processes are inherently dynamic (e.g., Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski, Gully, McHugh, Cannon-Bowers, & Salas, 1996; Kozlowski, Gully, Nason, & Smith, 1999; Marks, Mathieu, & Zaccaro, 2001; Mathieu, Maynard, Rapp, & Gilson, 2008; McGrath, Arrow, & Berdahl, 2000; Salas, Stagl, & Burke, 2004), they have been largely researched as static constructs – as a "box" in a model (Kozlowski & Chao, 2012b). The dynamics inherent in the conceptualization of team processes are largely missing in team effectiveness research (Cronin, Weingart, & Todorova, 2011).[1]

[1] The focus of this paper is on quantitative research. I readily acknowledge that qualitative researchers study process dynamics directly, much more so than quantitative researchers do (Kozlowski & Chao, 2012b). However, my focus is on mapping needed theoretical and research design advances for quantitative empirical research.

There are two primary ways that team process dynamics can be conceptualized. First, as group level constructs, team cognitive, motivational, affective, and behavioral processes *emerge* over time from individual interactions (Kozlowski & Klein, 2000). They do not simply spring into being. However, most research assumes a process of emergence has occurred and then simply treats the process as a higher level construct (Kozlowski & Chao, 2012). The "process" is static. Second, having manifest as collective properties, such phenomena can vary within teams, exhibit growth trajectories that increase or decrease in amount, or fluctuate cyclically with entrainment to other properties within or external to the team. These two primary process dynamics are only very rarely studied (Cronin et al., 2011).

There are undoubtedly many reasons for this state of affairs – and I will speculate about some of them – but *the key concern is to advance research that captures team dynamics*. I do not have a "silver bullet" or a singular solution, but I do offer several promising approaches for pushing research design and measurement to better capture the dynamics of team processes. McGrath consistently championed the need for team research to incorporate process dynamics. He was a prolific theorist on the topic, but the field did not follow (Cronin et al., 2011). For nearly two decades, my colleagues and I have theorized about team processes as multilevel phenomena that develop, emerge, and evolve over time (Kozlowski et al., 1996, 1999; Kozlowski & Klein, 2000). We, along with many others, have endeavored to directly study multilevel process dynamics with some limited success (e.g., Chen, Kanfer, DeShon, Mathieu, & Kozlowski, 2009; DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004). And, we are now embarked on several efforts to develop innovative research methods and measurement tools to capture multilevel team dynamics directly (e.g., Kozlowski & Chao, 2012a, 2012b). [2]

I will discuss three key themes in this paper. First, I will trace and speculate as to "how organizational psychology and behavior got here." Why does research overwhelmingly treat what is widely acknowledged to be a dynamic process as static?[3] That knowledge will not solve the problem, but it is instructive to have an appreciation of the factors that are responsible for a

[2] Small p for paradigm – an integration of theory, method, measurement, and analytics; not capital P – for scientific disciplines in the meaning of Kuhn.

[3] This problem extends beyond teams to process mechanisms more generally in organizational science, but the focus here is centered on team processes.

half century of inertia. Moreover, I think that perspective will make more salient the necessity that tackling this problem requires a substantial augmentation of our research methods and strategies, and much more theoretical precision. Second, I will discuss theoretical considerations that have to be surmounted to study the dynamics of team processes. Team processes are inherently multilevel phenomena that, shaped by the context, emerge bottom-up – individual to team – from team member interactions (Kozlowski & Klein, 2000); what Marks et al. (2001) characterize as "emergent states." However, team processes can also exhibit other dynamic properties such as variability, trajectories, and cyclical fluctuation. Theory has to be precise about the dynamics of interest if we are to advance understanding. Finally, we will not make progress until we develop innovative methods to capture team process dynamics directly. As an obvious point of departure, there are ways to adapt conventional research designs and measurement tools, and we should do that. However, I think real, frame-breaking advances will necessitate fundamentally different research design, measurement, and analytic approaches. These methodological and measurement advances focus on getting more data dense assessments of team phenomena that emerge, change, and evolve. For some this may raise concerns of parsimony and drowning in data. It is important to bear in mind that one can target and aggregate high frequency data to gain resolution on a phenomenon of interest, but one cannot get any resolution on the phenomenon if the data do not exist; the current status quo.

As I noted, I do not have all the answers, but there are some very promising approaches that merit consideration. That will mean taking a multidisciplinary perspective to advance our research and measurement toolkit so as to supplement tried and true methods. I will provide several examples that have potential to directly capture the dynamics of team processes. Consideration of analytic techniques is beyond the scope of this paper. However, relevant techniques include multilevel random coefficient modeling and latent growth modeling (MacCallum & Austin, 2000; McArdle & Nesselroade, 2003; Raudenbush, 2001), network analysis (Carley, 2003; Contractor, Wasserman, & Faust, 2006), and latent vector autoregressive and system dynamics analyses (DeShon, 2012; Hanges & Wang, 2012).[4] The

[4] DeShon (2012) and Hanges and Wang (2012) each provide an excellent introduction and overview.

more fundamental theory evaluation and research issues center on conceptualizing process dynamics and collecting data that are aligned with them. That is the focus of this paper.

Research on Team Processes

There are a variety of potential reasons why researchers treat team processes as static constructs, and my discussion is not intended to be exhaustive. I think there are two major influences[5] that have much to do with this state of affairs: (a) the broad influence of the IPO heuristic and (b) the development, rise, and widespread application of multilevel theory.

IPO heuristic. It is ironic that what is considered to be the dominant conceptual framework for studying team effectiveness – McGrath's (1964) IPO model – was not intended to be a causal conceptual framework – although it is treated that way by a multitude of researchers – and it was not intended to "freeze" processes into a mediating box – although that is what has happened. The heuristic was developed as a framework to organize the literature on small group research. At the time, much of the social psychological research on small groups was essentially bivariate. Researchers focused on I-P, P-O, or I-O (McGrath, 1997). The heuristic served to organize the research and to provide more coherence to the literature, albeit a static one. The irony is that McGrath was clearly on the cutting edge of trying to conceptualize team processes in dynamic ways. That is evident elsewhere in the same book (McGrath, 1964) and in subsequent theory (McGrath, 1990, 1991). Yet, it was the simple model that took hold and the conceptually deeper, temporally sensitive, more dynamic models have had far less impact.

Why? Here I speculate. First, the IPO model is intuitively appealing and easy to explain; it has a self-evident quality. Second, it is easy to implement as a conceptual model and research design architecture because it conforms well to dominant measurement methods (i.e., questionnaires) and analytics (i.e., regression-based mediation). It has also been amenable to more complex models that incorporate moderated-mediation or mediated-moderation, particularly as team effectiveness research grew in organizational psychology and behavior. As multilevel theory ascended, the IPO model was also amenable to contemporary multilevel random coefficient modeling analyses. Such flexibility is attractive and variants of the IPO

[5] Moreover, static research is far easier to conduct which, in combination with pressures for publication quantity versus quality, is another obvious factor. Deconstructing this issue necessitates an entire paper.

heuristic dominate the team effectiveness literature (Kozlowski & Ilgen, 2006). It is a useful, flexible, and powerful conceptual heuristic, but one that traps processes in a static box. It is, unfortunately, an unintended source of inertia.

Multilevel theory. Evolving from general systems theory and complexity theory (Kozlowski & Klein, 2000), multilevel theory applied to organizational systems developed independently and traveled its own path of transition from the periphery of organizational science (Roberts, Hulin, & Rousseau, 1978) to become a dominant mainstream influence (Kozlowski, 2012b). Multilevel theory is a meta theoretical framework, not a substantive theory. It shapes how one translates or situates substantive theory within a multilevel human system. It was for many years on the fringe of organizational research and fraught with considerable controversy with respect to theory, methods / measurement, and analysis. But, by the turn of the century, greater clarity in construct conceptualization and measurement (Bliese, 2000; Chan, 1998; James, Demaree, & Wolf, 1984, 1993; Kozlowski & Hattrup, 1992), the promulgation of principles to guide theory building and research design (Kozlowski & Klein, 2000), and advances in analytics (Bryk & Raudenbush, 1992; Klein et al., 2000) provided a foundation for guidance and models to emulate. Multilevel research exploded. Serendipitously, this research explosion coincided with the rise of team effectiveness research in organizational psychology and behavior. Teams are at the juncture of the macro context and micro individual characteristics; it is the meso level where team processes emerge. Team research became increasingly entwined with multilevel theory and research methods.

It is ironic that multilevel theory – which is fundamentally based on complex system dynamics – is largely applied to research in static ways (Kozlowski & Chao, 2012b). Does this sound familiar? There are two fundamental forces that operate in organizational systems: (a) top-down contextual effects that constrain or influence lower levels of the system and (b) bottom up emergent phenomena that – shaped by the context – evolve from the characteristics and interactions among individuals to yield team level properties. The study of contextual effects dominates in multilevel research and it is primarily conducted using cross-sectional designs. Emergence as a phenomenon for direct investigation (as opposed to an assumption or an inference) is largely unstudied and necessitates intensive longitudinal designs. As Kozlowski and Klein (2000) discussed and Cronin et al. (2011) documented, most quantitative research that considers emergence at all is focused on convergent composition forms. Emergence, which is inherently dynamic, is considered conceptually to provide a theoretical justification for the anticipated convergence of individual perceptions over time as they become a shared property of the team. That is, researchers assume convergence, evaluate it by assessing restricted within group variance, and then aggregate individual level data to the unit of interest. The *process of emergence* is almost never examined directly; it is an inference based on cross sectional data. Moreover, compilation forms of emergence that are likely more prevalent and important are largely neglected in research. Emergence as a core dynamic process in teams is rarely directly examined (Kozlowski, 2012a; Kozlowski & Chao, 2012b; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013).

Why? Here I speculate again. First, similar to the dominance of the IPO model, convergent forms of emergence – based on sharing – are intuitively appealing; they conform to our expectations about commonality and bonding processes in teams. Second, top down effects that shape convergent forms of emergence can be examined (with known limitations) in cross-sectional designs. Static designs dominate in organizational psychology and behavior research. Third, there existed a well-developed exemplar in the form of twenty years of climate theory and research. It provided theory that was flexible as to substantive content; it could be easily adapted to other topic areas within and beyond the boundaries of climate. And, it provided a well-developed research foundation with exemplars for design, measurement, and analyses that could be easily emulated. The result is a useful, flexible, and powerful conceptual approach, but one that is static. The modal application of multilevel theory (convergent emergence, top-down contextual effects, cross-sectional data) is another source of inertia.

Theoretical Considerations

Overview

Building on prior multilevel theory treatments (Chan, 1998; Kozlowski & Klein, 2000; Morgeson & Hofmann, 1999), Cronin et al. (2011) described three types of group and team level phenomena – *contextual, cumulative, and emergent* – relevant to process dynamics. *Contextual* phenomena, or what Kozlowski and Klein (2000) characterized as *global properties*, are unit level characteristics. They have no lower level underpinnings, so they are not the “stuff” of process dynamics. However, the context within which a team is embedded can change and that has direct implications for team processes. That is, processes may be influenced by a cross-level direct contextual effect. In addition, relations between team processes and antecedents or outcomes may be moderated by contextual factors. Thus, there are implications for team process dynamics that should be considered theoretically, particularly if the context is turbulent (e.g., medical teams, command and control, top management teams).

Cronin et al. (2011) characterize *cumulative* phenomena as a summary of individual level characteristics lacking interaction or a “synthesis function” (p. 575), what Kozlowski and Klein (2000) defined as *descriptive characteristics*. Cronin et al. (2000) view such phenomena as only minimally dynamic. They characterize collective team properties that may have implications for within team process dynamics (e.g., demographics, functional differences). Thus, collective team properties merit theoretical consideration, but they do not characterize the dynamics of team processes *per se*.

Emergent phenomena get to the core of team process dynamics directly. “Emergence describes a process where a higher level phenomenon comes into existence based on interaction among the lower level elements” (Cronin et al., 574). Kozlowski and Klein define it as: “*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)[6]. Core conceptual foci incorporated in this definition (Kozlowski et al., 2013) center on (a) the *multilevel* character of emergence in that the phenomenon originates within individual-level properties but manifests collectively, (b) *process mechanisms* that drive dynamic interaction and exchange and shape the nature of emergence, and (c) *temporal considerations* in that emergence unfolds over time. A theoretical consideration of the nature of emergence is critical to conceptualizing team process dynamics. Moreover, although phenomena that emerge in teams (e.g., team cognition, cohesion, conflict) are typically treated as static properties or constructs once they manifest, they may nonetheless exhibit dynamics in terms of within team variability over time (i.e., emergence is unstable), growth trajectories (i.e.,

[6] Italics in original.

linear increases or decreases in level, discontinuous shifts), and / or other types of fluctuation (i.e., cycles).

Thus, two conceptual considerations are necessary to capture these dynamics. One dynamic conceptualization is concerned with the emergence process of the phenomenon and its manifestation as a team property (or for composition, it's waxing and waning as a team property and / or for compilation, it's shifting configuration or pattern). A second conceptualization is concerned with dynamics of the phenomenon after it has emerged. These are not entirely distinct, but it useful to discuss them separately for clarity.

The Dynamics of Emergence

Emergence as a process can be conceptualized as two idealized endpoints – composition and compilation – spanning a continuum of emergent forms.[7] The underlying process mechanisms for composition forms of emergence are based on convergent dynamics. As individuals interact and exchange elemental content (e.g., cognition, affect, behavior), they become more homogeneous on the phenomenon of interest over time. Commonality, similarity, and sharing are characteristic of convergent process mechanisms. For example, team members working together collaboratively may develop a homogeneous knowledge representation of the task domain; a shared team mental model. In contrast, the underlying process mechanisms for compilation forms of emergence are based on divergent dynamics, whereby team member interactions yield heterogeneity over time. Such heterogeneity may be characterized by variability, disparity (i.e., conjunctive, disjunctive), or pattern / configuration. For example, the members of a collaborative team may differentially specialize in the knowledge to which they attend, compiling a differentiated transactive memory. Distinction, differentiation, and conflict, are characteristic of divergent process mechanisms.

Empirical research tends to treat these different emergent forms as static and invariant. Theoretical discussions of emergence for a given construct generally assume that the process evolves from individual differences in cognition, affect, and / or behavior to either composition or compilation forms at the collective level. For example, a team mental model is generally viewed

[7] I have discussed this extensively elsewhere (Kozlowski, 2012a; Kozlowski & Chao, 2012b; Kozlowski & Klein, 2000); this presentation is an abbreviated treatment.

as a composition form, whereas a transactive memory is viewed (conceptually) as a compilation form. This is largely a consequence of the practice of treating team processes as static constructs (Kozlowski & Chao, 2012b).

However, Kozlowski and Klein (2000) were explicit that forms of emergence are not necessarily fixed; "... *collective phenomena may emerge in different ways under different contextual constraints and patterns of interaction. Emergence is often equifinal, rather than universal in form"* (p. 59).[8] Thus, a phenomenon may emerge from the individual level to a compilation form that later evolves to a composition form, or vice versa. For example, in our research measuring and modeling team knowledge emergence, we observe a pattern of individual compilation to composition emergence. Through knowledge building, team members acquire distinctive knowledge about a problem space that yields a configuration at the team level (compilation). As members exchange their unique knowledge, it becomes a shared property of the team (composition) that can be applied to problem solving (Kozlowski & Chao, 2012a, 2012b; Kozlowski et al., 2013). *The implication is that process mechanisms underlying emergence must be explicitly specified theoretically and they must be explicitly measured and modeled in research*.

Team Process Dynamics

In addition to the processes by which emergent phenomena manifest in teams, team processes may exhibit other dynamics. Here I will discuss three potential types of process dynamics for a given phenomenon that focus on (a) within team variability, (b) growth trajectories, and (c) fluctuations over time.

Within team variability is related to the stability and / or form of emergence for a particular phenomenon. As part of the procedure for operationalizing a composition construct (e.g., shared mental model, team cohesion), researchers assess the degree of within team variance on the measure (i.e., variability across team members) using an index of agreement or inter-rater reliability as a justification for aggregating individual perceptions to the team level (Bliese, 2000; Chan, 1998; Kozlowski & Hattrup, 1992; Kozlowski & Klein, 2000). However, within team variability can also be treated as a *substantive characteristic* to index the extent to

[8] Italics in orginal.

which a composition construct has emerged (Brown, Kozlowski, & Hattrup, 1996; González-Romá, Peiró, & Tordera, 2002). Theory generally assumes that convergent interaction dynamics yield increasing homogeneity on a phenomenon over time. Thus, one would expect that multiple assessments of, for example, team cohesion would demonstrate a monotonic increase in the degree of within team agreement over time to a point at which sufficient convergence has been achieved to signal the manifestation of a team-level property (Kozlowski, 2012a). This pattern is illustrated in Figure 1a. One could directly track the process of cohesion emergence as a team level phenomenon.

High within team variance indicates a construct that has not emerged. However, emergence might be unstable. Consider the team cohesion example discussed above. Having emerged, now let us suppose that team members are under differential stressors or external events “shock” cohesion. The degree of within team agreement may decline, indicating that cohesion perceptions are no longer homogeneous. As the stressors abate, agreement again increases. The emergence of cohesion – the degree to which it is shared across the team – may be unstable. This is illustrated in Figure 1b. Emerged phenomena are not necessarily static and enduring; they are subject to internal and external shocks.

Alternatively, now let us suppose that cohesion emerges as a composition phenomenon, but then we observe not just an increase in within team variability to a degree that signifies a devolution from team-level to individual-level perceptions, but an increase that goes well beyond what would be expected due to random responding (i.e., disagreement) indicative of a qualitative shift in the team from convergent to divergent emergence (Brown & Kozlowski, 1999; Kozlowski & Klein, 2000). This would be indicative of a fragmenting or bifurcation of the team into factions. Assume that the cohesive team has two team members who become embroiled in an intractable relationship conflict. Through contagion, their colleagues take sides and the team polarizes. The pattern is one of compilation. This pattern of within team variability is illustrated in Figure 1c. This compilation configuration may become enduring, although it may possibly be shifted back to composition via conflict management interventions or external threats to the team.

<Insert Figures 1a, 1b, and 1c here>

Another dynamic pattern would be indicated by growth trajectories that capture a pattern of linear increase or decrease in the level or amount of an emerged property over time. The typical assumption is the level of cohesion in a well-functioning team would increase monotonically as shown in Figure 2a. In contrast, one could also imagine a team that is highly cohesive, but beset by a series of losses may exhibit a downward trajectory in the level of cohesion shown in Figure 2b. Alternatively, perhaps it is the case that initially a team converges on cohesion perceptions, but their collective assessment is that the team is only weakly or moderately cohesive. Then, the team goes through a series of “team building” experiences that bond members together or the team may need to achieve a superordinate goal that bonds the members tightly and quickly. We would observe a discontinuous shift in the level of cohesion illustrated in Figure 2c. Thus, different dynamic trajectories in the level or amount of team processes are possible.

Finally, there may be rhythmic or entrained cycles in process dynamics or, relatedly, reciprocal relationships. Imagine that a team is subjected to challenging working conditions. Workload is shared unevenly and not everyone contributes to common chores, pressuring team cohesion. However, once a week the team holds a communal meal, swaps stories, and has some fun. We would likely observe a cycle of cohesion fluctuation that peaks just after the positive event and then troughs on a weekly cycle as illustrated in Figure 2d. Indeed, we have observed very similar patterns in our research with extreme teams working in isolated, confined, and extreme (ICE) environments (Pearce, Rench, Braun, Baard, DeShon, & Kozlowski, 2012). Similarly, one could imagine how team cohesion and performance are reciprocally related. Higher cohesion helps enable collaboration that aids performance and performance reinforces cohesion. However, a series of performance failures could undermine cohesion which then contributes to lower performance. How can these dynamic process patterns be captured?

<Insert Figures 2a, 2b, 2c, and 2d here>

Methodological and Measurement Challenges

Measurement Methods

Micro-meso research is conducted by several disciplines within the broad sweep of the “behavioral sciences.” However, the vast majority of the “behavior” that is researched is based on self or other reports of internal states using retrospective questionnaires. It is a simple fact that reliance on questionnaires as the dominant form of measurement for team processes places significant limitations on efforts to capture process dynamics. Questionnaires take time to complete, are obtrusive, entail a variety of response biases, are potentially distorted by more frequent assessments, and are not necessarily accurate. I am not implying or suggesting that asking questions to assess team member perceptions, affective states, and other reactions should be discarded. However, I am asserting that such tools are inherently limited and at least need to be supplemented by other measurement methods that assess behavior in real time, are unobtrusive, are reliable, and can be captured at higher sampling rates. As I will discuss subsequently, there are a variety of measurement approaches that can meet this challenge including, task simulations, video capture, communications analysis, and behavioral sensors.

Sampling Rates

Processes have a rate of change and measurement periods have to be aligned or commensurate with that rate of change to capture process dynamics. Unfortunately, theories of team effectiveness and functioning lack precision with respect to temporal scaling and rates of process change. This imprecision is an operational challenge. If the rate of measurement is slower or lags the process rate of change, then one will fail to capture nuances in the change or may even miss important process phenomena. For example, if there is a tipping point or discontinuous shift in team processes between two widely spaced measurement periods, then one will not be able capture the process shift directly or to account for the mechanisms responsible for it. Similarly, if a phenomenon is oscillating in a waveform (e.g., sine wave cycle) and the measurement rate is not aligned, the data may reflect the top of the wave, the trough, or various points in between. The first two will make the phenomenon look high or low, respectively, and static; the third will make the level look random. The actual dynamic pattern will not be captured and interpretation and inference will be compromised. Capturing processes will generally require higher sampling frequencies than are typical in organizational psychology and behavior research.

If the rate of measurement is much faster than the rate of process change, then one will be able to capture process changes, but the design will be inefficient and there is the potential danger of drowning in data. On balance, this is preferable to missing observations, but it is also conditioned on the resources required to measure frequently and other potential costs. Resources are almost always limited in some way, so one would want to use them as efficiently as possible. Moreover, if measurement is intrusive (e.g., high frequency measurement with questionnaires), it may interfere with observation, change the nature of the phenomenon, or lead to participant withdrawal – all of which are undesirable. Furthermore, rates of process change may not be, and most likely are not, constant. Process dynamics may change in response to internal contingencies (e.g., a fluctuation in team cohesion based on team member conflict) or external contingencies (e.g., a change in coordination demands driven by wind shifts for firefighters or a patient that goes into arrest for an emergency medical team). Thus, generally speaking, high frequency measurement that is low cost and unobtrusive is highly desirable.

Descriptive Research

Micro-meso researchers are embedded in a theory-driven research culture. Scholars are expected to have a sound theoretical rationale to drive the data collection design and measurement frequency. Yet, theory is generally deficient with respect to time and dynamics. Most theories and research on team functioning are insensitive to temporal concerns (Mohammed, Hamilton, & Lim, 2009). Even those theories that incorporate a temporal component (e.g., Gersick, 1988, 1989; Kozlowski et al., 1999; Marks et al., 2001) do not specify the time scales[9]. On the one hand, that is unfortunate because it leaves researchers without specific guidance to specify a sampling design. On the other hand, such ambiguity should be expected because specific process dynamics will be strongly influenced by contextual factors, cumulative factors, and other local contingencies relevant to the phenomenon. Theory is not likely to resolve this ambiguity alone without assistance from data.

One broader research strategy that would begin to ameliorate this ambiguity would be to conduct systematic descriptive research on a phenomenon of interest. There is value for qualitative research in this regard, although good quantitative mapping is even better. For example, the time scales for team development are presumed to vary due to theoretically

[9] Gersick does, however, specify the developmental mid-point for the punctuated equilibrium, which is very useful information for guiding research design and measurement.

relevant contingencies – types of teams, tasks, contexts, and deadlines (Gersick, 1988, 1989; Kozlowski et al., 1999). There are many theories of team development. However, good, large sample, diverse team descriptive research is lacking. If the field were to compile a data base of well conducted descriptive research on team development and potential contingencies, we could – over time –develop benchmarks to guide research design and sampling rates. Unpublished descriptive research or qualitative observation will assist single investigators to tune their sampling plan. Published descriptive research on process emergence and evolution would help the field begin to develop temporal guidelines and would, in the long run, advance theoretical precision. Hambrick (2007) and others have called for more openness to the value of descriptive research in organizational science. Some journal editors have explicitly called for good descriptive research on temporal processes (e.g., Kozlowski, 2009). Special issues and new journals open to such research perhaps signal a shift in the pendulum, so longer term there may be more information, empirical guidance, and research precision for aligning sampling rates with dynamic phenomena. For now, however, I assert that cheap, frequent, and stealthy comprise the key elements of an effective strategy.

Capturing Team Dynamics: Adapting Methods, Creating Innovative Tools, and Advancing New Paradigms

Overview

The process dynamics I have mapped cannot be captured using minimalist longitudinal designs with three measurement periods. Indeed, even repeated measures designs with five, ten, or twenty measurements – while useful as a point of departure and to build knowledge – are not adequate for fully unpacking process dynamics. There is a need for “intensive” longitudinal designs that entail at least thirty and preferably many, many more measurements (Walls & Schafer, 2006). Such designs are not unknown in organizational psychology and behavior research, but they are certainly not highly prevalent. They pose real challenges for laboratory experiments and even more serious difficulties for field research. Advancing research on team dynamics necessitates that we (a) adapt and extend existing methods to get better resolution, (b) create innovative measurement tools to enable the capture of high frequency sampling rates, and (c) advance new paradigms for research that better map team process dynamics and their mechanisms. All three approaches are needed to advance understanding.

Adapting and Extending Research Methods

In this discussion, I consider laboratory methods (dedicated research simulations), lab and quasi-field methods (off-the-shelf simulations and games), and field methods (experience sampling). What sort of team processes would be appropriate for these methods? To answer this question, it is useful to consider appropriate boundary conditions. For dedicated research simulations, the teams of interest will typically be ad hoc groups without any prior history or future beyond the research. For off-the shelf simulations and games, the teams may range from ad hoc groups, to student teams working across a semester long simulation, to self-forming on-going teams involved in a massively online gaming community. Clearly, these represent different research environments that have to fit or have “psychological fidelity” (Kozlowski & DeShon, 2004) with the phenomenon of interest.

The phenomena of interest would have to develop, evolve, emerge, and / or fluctuate to some meaningful degree within the limited temporal confines of the study. Thus, the process dynamics of the phenomena under investigation would have to fit with these constraints for the research to be meaningful. In my opinion, the dynamics of many of the team process phenomena identified by Kozlowski and Ilgen (2006) as relevant to team effectiveness could be examined. Relevant targets would include team cognitive factors (i.e., team climate, mental models, transactive memory, knowledge acquisition and learning; DeChurch & Mesmer-Magnus, 2010a, 2010b), motivational and affective factors (i.e., team cohesion, efficacy, potency, trust, and conflict; Dierdorff, Bell, & Belohlav, 2011; Lanfred, 2007), and behavioral factors (i.e., team process behaviors, regulation, and adaptation; Chen et al., 2009; DeShon et al., 2004;). These team processes have the potential to develop, at least initially, over relatively short time periods appropriate to lab simulations and to exhibit longer term dynamics that would be appropriate in field research. The key challenge is to match the research design to the phenomenon of interest so as to capture team dynamics with good resolution.

Dedicated research simulations. There are several well-developed team simulations represented in research that have the potential to illuminate team process dynamics. They have not generally been so used, but they have that capability. Here I illustrate a few notable applications so interested readers can follow up to discern the potential in such tools. I then highlight advantages and limitations of this approach. All of these applications were purpose-built to investigate a particular aspect of teamwork; they represent *research paradigms* – an alignment of theory, simulation design, measurement, and analytics.

Hollenbeck, Ilgen, and their colleagues (Hollenbeck, Sego, Ilgen, & Major, 1991) developed the *Team Interactive Decision Exercise for Teams Incorporating Distributed Expertise* (TIDE^2); a computer-based simulation for studying team decision making. TIDE^2 was based on an integration of multiple cue probability learning and a multilevel theory of leader decision making in hierarchical teams (Hollenbeck, Ilgen, Sego, Hedlund, Major, & Phillips, 1995). Although TIDE^2 has the potential to generate data to capture dynamic processes relevant to team decision making, it has not tended to be used for that purpose. Perhaps the closest exemplar is research by LePine (2005), who examined role adaptation in teams following a disruption to the communication structure. Even though LePine (2005) assessed team performance longitudinally for 50 trials post-disruption, process mechanisms and dynamics were not directly assessed. Later work by Hollenbeck and his colleagues adapted a different team simulation, Dynamic Distributed Decision-making (DDD). MSU-DDD was used to study asymmetries in structural adaptation (e.g., Moon, Hollenbeck, Humphrey, Ilgen, West, Ellis, & Porter, 2004) as well as phenomena related to cooperation and competition in teams (e.g., Beersma, Hollenbeck, Conlon, Humphrey, Moon, & Ilgen, 2009). Again, there is potential to use the simulation to study dynamic processes, although that has not tended to be a primary research focus.

Kozlowski and colleagues adapted a team decision making simulation that was originally developed by the Navy (TANDEM) to develop a paradigm for studying individual self-regulation, learning, and performance adaptation (Bell & Kozlowski, 2010; Kozlowski & Gully, 1996). Further development extended the simulation – Team Event-Based Adaptive Multilevel Simulation (TEAMSim) – to examine multilevel (individual and team) regulation, learning, adaptation, and performance (DeShon et al., 2004; Kozlowski & DeShon, 2004).The research was predicated on a model of multiple goal regulation (individual and team goals) and the mechanisms by which dynamic goal regulation by team members yielded an emergent homologous multilevel model of team regulatory processes (DeShon et al., 2004); that is, parallel models of individual and team goal regulation. Data were collected across twelve scenarios (in blocks of two trials for six waves of data) and was analyzed using multilevel random coefficient modeling (MRCM). Although the theoretical underpinnings of the model were dynamic, the micro dynamics could not be directly exploited in the data. Essentially, MRCM averages over the trials; this is a theme in most of the analyses I describe. Yet, the potential to capture team process dynamics is there with more slices of data.

Research by Chen and colleagues (Chen et al., 2009) reanalyzed these data, and other data (Chen, Thomas, & Wallace, 2005), to evaluate a multilevel model of motivation in teams. Whereas the prior research focused on multilevel homology (Chen et al., 2005; DeShon, 2004), this work examined how – having emerged from the individual to team level – collective team process constructs exerted a top-down constraining effect on subsequent individual motivational processes and performance. Looking across the two sets of research, one can extrapolate the reciprocal processes of bottom-up emergence that subsequently create top-down contextual constraints shaping lower level process dynamics. MRCM was used for analyses and, again, micro dynamics could not be directly exploited, but they are tantalizingly close.

Dedicated research simulations offer investigators many key advantages. They are grounded in theory. Thus, the alignment of research design and theory is built into simulation design. The simulation is purpose built, thus its ability to capture a particular aspect of team process dynamics can be optimized. The data are rich, copious, and detailed. Computer-based simulations typically collect keystroke level data. Such data are behavioral, unobtrusive, and at very high sampling rates. These features make such paradigms very powerful research tools with high potential for capturing team process dynamics.

Of course, such strengths have off-setting limitations. Simulation paradigms are purpose-built to investigate specific team processes. They may have some flexibility, but they are generally limited to a small range of phenomena. Building a research paradigm is resource intensive in both intellective and material terms. One has to be able to conceive it and then create it. Building it requires funding to support programming, a substantial laboratory infrastructure and research assistants to run it, and a system for recruiting participants. Finally, such tools have limited availability. Even if one can acquire existing simulation software and build infrastructure, the learning curve is considerable. Such tools are not for the faint of heart! That fact is not meant to be discouraging. On the contrary, chose your target process well, then build the infrastructure, and finally study the space systematically. That’s a hallmark of science.

Off-the-shelf simulations and games. There are a variety of team-based computer or console games that are primarily used for entertainment, and simulations that are typically designed for education, that have potential as useful methods for capturing team dynamics. They are not the best approach – dedicated research-based simulations are better – but they are accessible to a wide range of researchers, require less extensive infrastructure, are cost effective, and exhibit demonstrated potential for useful application.

For example, Mathieu and colleagues (Mathieu, Cobb, Marks, Zaccaro, & Marsh, 2004) modified a commercial F-22 air combat game to create a low-fidelity simulation – Air Combat Effectiveness Simulation (ACES) suitable for examining multi-team systems (MTS). Research by Marks, DeChurch, Mathieu, Panzer, and Alonso (2005) assessed “… how both cross-team and within-team processes relate to MTS performance over multiple performance episodes ….” (p. 964) that is consistent with the Marks et al. (2001) transition-action model of team processes. This research used two dyads to simulate the MTS, with each team performing a different role (air vs. ground) that required interdependent action. Teams were videotaped. Action and transition processes were coded from the video. Team performance was provided by metrics from the simulation. Each team performed three scenarios and analyses utilized repeated measures multiple regression (RMMR). In such an analysis, within team variance represents team dynamics. So, like prior research (i.e., DeShon et al., 2004), dynamics are there, but they are indirect and stealthy.

Research by Dierdorff et al. (2011) used a business simulation (Capstone Business Simulation; D. Smith, 2008) to examine the influence of psychological collectivism on team performance at three distinct points in time: early, end-state, and change over time. Participants were enrolled in a business course, played the roles of upper management, competed against other teams for market share, and had a portion of their grade determined by their simulation performance. The game simulated 8 years of activity and was conducted across a five week period. Although there was a temporal aspect to this research, team processes per se were not a research target. Team member exchange (TMX) was assessed at three points in time, but it was treated as a moderator. Analyses were conducted using multilevel latent growth modeling (LGM) to examine within team change and differences in between team performance (i.e., early, end-state, and change trajectories). Thus, there is an effort to capture dynamics, but it is again indirect.

Randall, Resick, and DeChurch (2011) used Sim City 4 (Deluxe Edition, EA Games, 2004) to study the effects of leadership (sensegiving) and team composition on collective information processing. The research was consistent with adaptability paradigms where, after a period of learning and development, some feature of the task environment abruptly shifts and the team has to adapt its strategy to the changed characteristics. In this research, three person teams collaborated to build a simulated city under one set of constraints that required particular strategies for success. Then they were switched to manage a city under a very different set of conditions and therefore had to adapt their strategies. Performance was indexed by Sim City 4 data (i.e., population growth), whereas “team process” measures were collected via questionnaires and by video coding of team member decision phases. Although it may have been possible to extract some dynamic processes from the decision phases, the analysis treated team processes as static structures in a structural equation modeling (SEM) analysis.

Off-the-shelf games and simulations offer investigators several attractive advantages for studying team dynamics. They are engaging and immersive, making participant recruitment, motivation, and persistence relatively less challenging than is the case for research-based simulations. Indeed, for Internet-based games, investigators can tap into an existing and ongoing player community to recruit teams of highly motivated participants that are not saddled with the limitations of ad hoc lab teams (e.g., Korsgaard, Picot, Wignad, Welpe, & Assmann, 2010; Pearce, Rench, Braun, Firth, Baard, DeShon, & Kozlowski, 2011). In that sense, these simulations offer a range of design flexibility from use in a contained lab with composed teams (to control procedures and to supplement measurement, e.g., Randall et al., 2011) to a quasi-field design where teams are composed naturally and data collection is completely virtual (e.g., Korsgaard et al., 2010). Moreover, these simulations are widely available, and resource costs and infrastructure requirements are low. Indeed, for on-line games, participants provide their own experimental platform (i.e., computer or game console, software, connectivity) and are willing to participate repeatedly over lengthy periods of time. What's not to like?

Of course, there are off-setting disadvantages that have to be effectively managed. Off-the-shelf games are not developed as part of a paradigm. No theory guided game design. That means investigators have to carefully align their theory and research design with the way in which the simulation creates an interactive experience. Moreover, whatever behavioral metrics might be available were not designed to tap constructs or relevant team process dynamics. Indeed, there are typically no metrics available from the simulation to capture team processes; thus investigators have to supplement the simulation with observation, video coding, and / questionnaires. Care in capturing team process dynamics with supplemental measurement is critical to effective use of these tools.

Experience sampling methodology (ESM). ESM, or what is also described as Ecological Momentary Assessment (EMA), was developed as a research design to capture the variability and dynamics of within-person psychological experiences *in situ*. Although there were a variety of influences that yielded the development of ESM, early work by Csikszentmihalyi and his colleagues (e.g., Csikszentmihalyi, Larson, & Prescott, 1977; Larson & Csikszentmihalyi, 1983) is generally credited with the origin of the technique (Hormuth, 1986). In typical applications, ESM involves a participant responding to daily – or many times daily – questions regarding the nature of their psychological experiences. The assessments are momentary "snapshots" of experience that can be interval-contingent (i.e., at pre-established time lags or particular times of the day), event-contingent (i.e., following a particular trigger stimulus), or signal-contingent (i.e., random via a prompt from a signaling device; Uy, Foo, & Aguinis, 2010). Data can be collected via paper and pencil diaries, Internet-based surveys, and / or digital devices (i.e., previously a personal digital assistant [PDA], now mobile apps), so it is quite flexible.

Penetration of ESM into organizational psychology research was energized by Affective Events Theory and, thus, most studies focus on within person variation in affect, mood, and emotion (Beal & Weiss, 2003). Remarkably, almost all of this research focuses on individuals or couples; almost none of it – at least none that I could locate – examines within team process dynamics. That is unfortunate because, extrapolating from within-person research, one can anticipate its potential. For example, Beal, Weiss, Barros, & MacDermid (2005) used ESM in an effort to capture cyclical dynamics between affect and performance, arguing that work is composed of a series of “performance episodes” that are “… naturally segmented, relatively short episodes thematically organized around work-relevant immediate goals or desired end states” (p. 1055). Notice that this episodic perspective is highly similar to the conceptualization of teamwork processes (e.g., Kozlowski et al., 1996, 1999; Marks et al., 2000; McGrath et al., 2000). Thus, one can envision a number of advantages for the application of ESM to study the dynamics of teamwork.

For example, ESM can enable investigation of team process dynamics in the wild – *in situ* – for teams that are embedded in a consequential work context and that are meaningful social entities; that is, they have a past, present, and future. Moreover, ESM enables longitudinal sampling over time at rates that are necessary for the application of dynamical analyses (DeShon, 2012; Walls & Schafer, 2006). Such research would represent a major advance for descriptive or theory-driven research on team process dynamics. In research I am conducting with colleagues, we have been using ESM to capture team cohesion and conflict dynamics in isolated, confined, and extreme (ICE) environments, namely Antarctica. The science teams we have been studying provide daily ESM entries while deployed on the ice for upwards of six weeks during their mission. Sample sizes are small, but daily entries provide over 40 longitudinal assessments of team member states. Thus far, the data indicate considerable variability in team cohesion over time both within and across teams (Pearce et al., 2012). Emergent states are quite variable.

However, there are substantial challenges for utilizing ESM (Beal & Weiss, 2003; Scollon, Kim-Prieto, & Diener, 2003), which is perhaps why this approach has not been widely used for team research. First, ESM is resource intensive. It requires time, effort, and consistent responding by respondents. If technology is involved, there may be infrastructure costs and training could be necessary. Second, sample sizes tend to be small, although statistical power is inherent in the many repeated measurements. Participant noncompliance (i.e., failure to respond) and withdrawal are also problematic. Team research would exacerbate problems due to sample size, noncompliance, and withdrawal. The effects of failure to respond and withdrawal would be magnified at the team level. Third, sampling rates – even though they could be very high relative to other approaches – may still lack sufficient resolution to adequately capture process dynamics. This is a sampling rate issue where the frequency of assessment has to be commensurate with the rate of change in the phenomenon of interest. Thus, daily ratings or a few ratings per day could be informative. However, it is also very likely that meaningful micro dynamics would be missed. Finally, because of intrusiveness, one can only ask a few focused questions per assessment, so the research needs to be very precise; breadth is challenging.

Developing Innovative Tools for Measurement

It is because of these challenges that innovative measurement techniques that are unobtrusive and have the potential to provide continuous or near continuous assessments – *not snapshots, but movies* – hold great promise. My treatment in this section is not intended to be exhaustive. Rather, the intent is to sample a small number of promising approaches that can be easily utilized (e.g., video recorded behavior) or that are under development (e.g., behavioral sensors) but hold promise for the future. The main point I want to get across is that researchers should *routinely* seek to supplement questionnaire based assessments with alternative measures of behavior. Although this is critical for research on team process dynamics, I think it is important for enhancing the quality of measurement across the broad sweep of organizational psychology and behavior research.

There is a caveat. Behavioral measures are not useful for assessing just anything. The behavior that is assessed has to be manifestly diagnostic of the construct of interest. The less inference regarding the meaning of the behavior by a coder or rater, the better it is for construct validity. Given that team processes span cognitive, affective, motivational, and behavioral domains (Kozlowski & Bell, 2003), calibrating how behavioral artifacts can clearly and cleanly capture a phenomenon of interest remains paramount. As team members collaborate, they will often communicate explicitly to share knowledge and cognition via verbalizations or electronic communication (e.g., chat, e-mail). Affective reactions can be revealed by explicit communication and behavioral reactions. And, of course, motivation in the form of performanceoriented effort and transition / action processes has behavioral artifacts (i.e., coordination, back up). Thus, there are a variety of ways that team process dynamics can be meaningfully captured via behavioral assessments.

Video/audio-recording. Perhaps the most straight forward way to *collect dynamic data* is to simply video and audio record teams as they engage in collaborative tasks. Of course, collecting such data is easy, the real challenge is devising construct valid coding or rating schemes to translate observations into meaningful measures of team processes. Doing that in such a way that dynamics can be extracted necessitates sufficient granularity in the behaviors that are coded. I had previously described laboratory research using off-the-shelf simulations that supplemented measurement of team processes using video recording (Marks et al., 2005; Randall et al., 2011). Independent observers later rated the video to provide overall assessments of transition / action process dimensions.

To apply this approach, an investigator needs to identify the process dimensions of interest. The Marks et al. (2001) typology provides a theoretically based set of relevant team behavioral process dimensions. Meta-analytic support for the typology and its structure (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008) provide evidence for their validity and generality (Fernandez, Kozlowski, Shapiro, & Salas, 2008). Research that my colleagues and I are conducting, which examines processes and performance in emergency medical teams, uses a high fidelity patient simulator, scripted event-based scenarios, video and audio recording of team processes and performance, and independent behavioral coding of team process behaviors (i.e., psychology coders) and performance actions (i.e., medical coders) to capture the dynamics of the team as they grapple with stabilizing the simulated patient (e.g., resuscitation and cardiac arrest).

This approach to video data capture is part of a paradigm in that it is highly integrated with the other components of the research. Medical cases were used to identify key teamwork problems and events, simulation scenarios were constructed to present a representative series of events, specific behaviors (i.e., actions, verbalizations, timing) for resolving events were mapped to team process dimensions, all components were evaluated for content validity by medical or teamwork subject matter experts (SMEs), and video coders were highly trained and monitored for calibration and reliability (Grand, Pearce, Rench, Chao, Fernandez, & Kozlowski, 2013). This approach allows for an examination of how different team processes are differentially relevant to team effectiveness as the scenario unfolds. Process and performance dynamics can be mapped (Grand, Pearce, & Kozlowski, 2013).

Thus, video and audio recording are highly flexible forms of data collection. By definition, they capture team process behavior as a stream of continuous data. Thus, they have high potential for mapping the dynamics of team processes. The cost for basic recording technology is relatively low, the technology is easy to use, and copious amounts of data are easy to collect. The raw video and audio have to be translated into meaningful assessments, but measurement is a core capability of organizational psychology. The coding systems that translate raw video and audio into meaningful data can range from simple to complex, broad to highly granular, and static to dynamic. It is a matter of what an investigator wishes to examine and how the assessment system is constructed (Grand, Pearce, Rench et al., 2013).

Given this flexibility and the advantages of this approach, one might wonder why it is not used more widely. Effective coding / assessment systems are laborious to design, build, validate, and utilize. It is a lot easier to just ask questions. Yet, there is hope for a less laborious application of video-based assessment. There are a variety of exemplars that use software to automatically code video behavior (either in real-time or with post processing). Most of these examples are at the individual level, but as the technology, software, and algorithms improve it should be straight forward to generalize them to team settings. For example, Liu, Zhang, Yadegar, and Kamat (2011) describe a system that is designed to categorize emotional responses based on automated analysis of video-based behavioral cues (i.e., facial expression, body posture). In the future, there will still be a central role for rigorous measurement development, but much of the labor for data classification may be augmented or automated by technology, software, and computing power.

Communications analysis. In addition to behavioral expression, team members often rely on verbal or written information exchange as the behavioral mechanisms for expressing team processes. Communications analysis is not widely used as an assessment method in organizational psychology and behavior research, but it is used elsewhere (e.g., communications and computer supported cooperative work [CSCW]) and it offers much potential for team researchers.

One of the key challenges of coding communications data is extracting meaning from the use of particular words in the context of the discourse (Rose, Wang, Cui, Arguello, Fischer, Weinberger, & Stegmann, 2008). Early efforts to augment the "hand coding" of a corpus of communications by automated content analysis tended to rely on dictionary-based approaches, such as Linguistic Inquiry and Word Count (LIWC; Pennebacker, Francis, & Booth, 2001). Although such approaches are reported to work well to capture emotional states in very specific contexts, their effectiveness in more naturalistic settings is problematic. As noted by Rose et al. (2008, p. 239), "… the words "bake" and "roast" used while talking about the weather convey a feeling of discomfort, whereas in the context of a discussion about cooking, they do not." Thus, there is a need for more contextually sensitive classification systems and computational modeling tools (Rose et al., 2008).

Taking a related but different approach, Miller, Wu, and Funk (2008) are developing a set of communication-based assessments and computational models designed to monitor the quality of social interactions – specifically in terms of politeness – that undergird team processes and performance. The researchers contend that politeness represents "… the processes by which we determine and manage the threat inherent in communication between intentional actors, who are presumed to have goals, and the potential to take offense at having those goals thwarted" (p. 2). Grounded in Brown and Levinson's (1987) theory of politeness, the computational model scores "face threats" which occur during the course of a social interaction that either support or undermine team processes. Relevant linguistic indicators can be extracted from automatically transcribed audio communication, chat logs, or email exchanges. Subsequent work has adapted these computational algorithms to capture "regard networks" from communication exchanges to augment traditional social network analysis (Miller, Schumer-Galunder, & Rye, 2010). In the long term, this line of development may integrate other behavioral data streams such as the facial expression, posture, and verbalization cues incorporated in the emotional recognition system described previously.

Behavioral sensor systems. This last example of innovative tools is on and just a bit over the horizon. In addition to the use of video, audio, and text to capture human behavior that I highlighted above, there is a wide array of technologies that can capture different behavioral components of complex interactions and exchange. By combining these component technologies into an integrated sensor platform, one can create a technology system that captures team member interactions and exchanges. Perhaps the most visible of these efforts has been the work of Pentland and his colleagues at the MIT Human Dynamics Laboratory.

On the horizon, Pentland and colleagues have been developing a sociometric badge – a wearable wireless sensor array – that is designed to assess multimodal data to characterize the nature of human social interaction and collaboration (e.g., Olguin, Gloor, & Pentland, 2009; Olguin, Waber, Kim, Mohan, Ara, & Pentland, 2009). Among its other capabilities, the sensor array captures identity, movement and physical activity, face-to-face interaction and proximity, and vocalization. By combining these data streams, one can capture team interactions with rich data (Kim, McFee, Olguin, Waber, & Pentland, 2012). Research using the badges has been conducted in a variety of organizational settings. For example, one study examined 67 nurses in a hospital across 27 days as they interacted with each other and with patients. Another study examined the interactions among 22 employees in the marketing department of a bank over the course of 20 working days. Thus far, the research has primarily been descriptive in nature, with many suggested applications offered for the technology. This technology is commercially available for interested researchers.

A bit over the horizon, my colleagues and I are working with an engineering team to develop a similar technology that can monitor team collaboration processes in real-time with high reliability and accuracy (Baard et al., 2012; Kozlowski et al., 2012; Quwaider & Biswas, 2010). The sensor platform is packaged as a wearable “badge” that assesses team member identity, face-time distance and duration, physical motion, vocal intensity, stress, and heart rate (HR) and HR variability. The multimodal data streams are sent via a wireless link to a computer or the “cloud” for data recording. The technology samples the respective modalities at extremely high sampling rates such that, for all practical purposes, the data streams are continuous. The goal of this research is to develop the technology platform, measurement tools, and analytics into an integrated system that can capture team interaction processes in real time, provide feedback, and even interventions so team members can regulate the effectiveness of their collaboration and cohesion processes (Kozlowski, Biswas, & Chang, 2013; Kozlowski et al., 2012).

These innovative technologies are designed to be unobtrusive, high frequency, data dense, and near continuous measurement systems. Learning how to use them effectively to conduct research on the dynamics of team processes will necessitate that we also extend our knowledge of measurement design to fuse the multiple data streams into a coherent assessment of team member and team functioning (Kozlowski et al., 2012) and analytics to exploit the dynamics inherent in such data (DeShon, 2012). Lest you think this effort is too far *over* the horizon, bear in mind that many millions of people around the world are carrying smart phones that act as multimodal sensor platforms right now. These devices are streaming data that report location, movement, proximity, preferences, and purchases. Those data are being mined and interpreted to market products and services. We need to be harnessing these technologies to advance research design and understanding about human interaction.

Creating New Research Paradigms

Overview. Sensor platforms are on and over the horizon. Another research design approach – computational modeling that couples theory building and virtual experimentation with human research for verification – is also poised to substantially advance the ability of researchers to probe the dynamics of team processes. Over a decade ago, Hulin and Ilgen (2000) advanced computational modeling as the “third scientific research discipline” (p. 7) to augment the primary reliance on experimental and correlational designs in organizational psychology and behavior research. Computational modeling is used effectively in many fields of research, but it “… is the “red headed 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). Although it is often used for macro system modeling (Miller & Page, 2007), its use in micro-meso research – with few exceptions – is little changed over the first decade of this century. Verification of modeling findings has been a stumbling block, especially for the modeling of large-scale systems (Epstein, 1999). However, this challenge is more tractable for teams. Here I argue for the value of building new research paradigms based on computational models, agent-based simulation for virtual experimentation, and human research for verification.

Computational modeling and agent-based simulation. A computational model is a theoretically based model of the process mechanisms underlying a dynamic phenomenon. The "word theories" that are commonly used in organizational psychology and behavior endeavor to do the same thing, that is, articulate process mechanisms. The difference is that a computational model specifies the process mechanisms with great precision, that is, mathematically (i.e., as equations or logical if-then conditions) to describe changes in system state from one time point to the next time point (Harrison, Lin, Carroll, & Carley, 2007; Hulin & Ilgen, 2000). Weinhardt and Vancouver (2012) provide an excellent introduction to computational modeling and its potential applications to individual level process dynamics. Computational models also have powerful potential for modeling team and higher level system dynamics (Kozlowski et al., 2013).

Computational modeling fits well with the complexity theory underpinnings of emergence (Kozlowski & Chao, 2012b,). At its core, the basic concept is that a small set of fundamental process mechanisms, principles, or rules that govern the interaction of system elements, can yield complex system level behavior. I frequently use an example from Reynolds (1987) on flocking in birds – BOIDS – to illustrate this powerful concept because it is simple, clear, and compelling. There are three fundamental rules that underlie the process mechanisms of flocking that govern the behavior of boid agents: (1) stay away from other boids to prevent collisions (separation); (2) travel in the average direction of the flock (alignment); and (3) move toward the center of the flock (cohesion). When these computational rules are programmed into an agent-based simulation, the implications of the rule set for system dynamics can be illustrated. Each agent is programmed to maximize its rule set or goals, in dynamic interaction with the other agents each also attempting to maximize goals. The result is remarkable fidelity between boid flocking and bird flocking. Recall the previous discussion of emergence. Individuals, in interaction with other individuals, shape the emergence of higher level phenomena; a few simple rules can create complex process dynamics, emergence, and system-level behavior.

As organizational science seeks to extend understanding of system processes at multiple levels of the organization, researchers must grapple with the dynamics inherent in human behavior, its emergence to higher system levels, and the evolution and fluctuation over time that are inherent in process dynamics. They must account for stochastic shocks, recursive and cyclical relationships, and path dependence (Cronin et al., 2011; Hulin & Ilgen, 2000). Even with the most advanced extensions to the two dominant scientific disciplines – experimental and correlational designs – noted previously, those methods are severely limited in their ability to map process dynamics. As Hulin and Ilgen (2000, p. 6) note, the data for these dominant designs are largely "… observations across a limited and arbitrary time interval; they are snapshots of a stream of behavior whose headwaters and destination are unknown. The settings for the pictures are determined by ease of access to the banks of the stream. These snapshots do not allow dynamic causality to unfold across time at its own cadence." There is a unique role for computational modeling – in combination with existing methods – to help peer into the black box of process dynamics (Harrison et al., 2007). Using it effectively necessitates that we create new research paradigms (Kozlowski & Chao, 2012b; Kozlowski et al., 2013) to exploit it effectively.

Computational modeling offers several compelling advantages for advancing research on multilevel dynamic processes. First, it requires theoretical precision and parsimony. Theory regarding the process mechanisms that drive emergence dynamics has to be sufficiently well-developed that it can be formally specified. Specification is aided by parsimony. The goal is to model the dynamics of the system with as few fundamental mechanisms as possible. Later, complexity can be incremented. This approach is somewhat at odds with prevailing scholarly norms that emphasize deep, richly articulated, and complex "word based" theories. Many words are required because it is challenging to convey clearly the intended meaning of the rationale. Formal specification applies Ockham's razor to such theories, necessitating that we focus on fundamental mechanisms that drive team process emergence and dynamics. Second, time frames (i.e., how long), sampling rates (i.e., how often), and sample size (i.e., how many) are virtually unconstrained; limited only by computing power. This enables essentially unlimited "virtual experimentation" across all theoretically relevant contingencies (i.e., contextual variation) of a model space. One can run two, ten, or fifty conditions simultaneously. This is a major strength compared to traditional designs (Kozlowski et al., 2013).

Computational modeling also has some challenging limitations, which is perhaps why it is not used very much in organizational psychology and behavior research. First, one must be able to specify the process mechanisms that drive the dynamics of the phenomenon mathematically, logically, or functionally. As noted previously, that is challenging for word based theories that are not process or time sensitive. Notions of what constitutes "good theory" and how it is expressed would have to evolve, although this is a desirable evolution. Second, once a model has been specified, one needs to obtain parameter values from the research literature to operationalize agent-based simulations. Because processes are not directly studied in our literature, this can be challenging, but this too is tractable Third, model verification can be difficult. Fidelity – that the results of a model are similar to the actual phenomenon – is not evidence for validity. For example, birds do not necessarily interact in flocks to maximize boid rules. Fidelity makes the three boid rules good candidates, but they need to be evaluated against other competing rules. Verification and validation with real world data are necessary (Hulin & Ilgen, 2000).

For macro system modeling, verification can be very difficult or impossible because of the demands on the necessary verification data. For micro-meso modeling, however, one can integrate computational modeling with conventional research designs to create a hybrid approach. In this hybrid, a computational model instantiated in an agent-based simulation, is used to conduct virtual experiments. Theory-driven virtual experimentation allows an evaluation of the "generative sufficiency" of the process mechanisms (Epstein, 1999). Promising top-down effects and contingencies (i.e., direct and moderating contextual factors) and potential points of leverage that shape the process mechanisms can be identified. Then, experiments based on observations of human behavior can be used to refine parameter values, verify and validate predictions, and – importantly – update and refine the computational model. Successive cycles of virtual research, human research, refinement and extension provide a powerful paradigm that – within its constraints – can substantially advance theory and understanding on team process dynamics (Kozlowski et al., 2013).

My colleagues and I have developed just such a paradigm to study the dynamics of team learning and knowledge emergence. It is theory-driven. It is based on a synthesis of multilevel theory (Kozlowski & Klein, 2000) and macrocognitive process theory (Fiore, Rosen, Smith-Jentsch, Salas, Letsky, & Warner, 2010). Macrocognition is the process by which team members acquire distinctive knowledge, combine it to build a shared representation, and apply it to solve consequential problems. We developed a multilevel measurement typology that is designed to capture the dynamics of team knowledge emergence as it evolves from individual knowledge (a compilational, configural structure) to patterns of shared dyadic knowledge and then emerges as actionable team level knowledge (a compositional, shared structure) over the course of problem solving (Kozlowski & Chao, 2012a). To exploit this measurement typology, we developed a computational model instantiated in an agent-based simulation and coupled it with a human-based decision making simulation – CRONUS – that captures this dynamic process of knowledge emergence in teams (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2012b). We are now engaged in research that utilizes agent-based simulation as a theory-building tool, and CRONUS as a means to verify those modeling predictions in human behavior.[10] Initial findings have been promising. Findings derived from agent-based modeling have been used to guide the design of interventions that target human learning and knowledge building in teams with good effects.

Discussion

Process Dynamics: The Next Frontier

Over sixty years of research on team processes and team effectiveness have yielded a wealth of actionable knowledge (Ilgen et al., 2005; Kozlowski & Bell, 2003, 2012; Kozlowski & Ilgen, 2006; Mathieu et al., 2008; Salas et al., 2004). The research foundation is clear that team processes are an important contributor to team effectiveness. Yet, it is also clear that our knowledge of team processes – which are inherently dynamic – is limited to static concepts. We really do not understand team process phenomena because their dynamics are largely unstudied (Cronin et al., 2011; Kozlowski & Bell, 2003). That is beginning to change.

[10] The specifics for “how to” build this paradigm MAY BE described in detail elsewhere in this special issue.

There is a confluence of influence from several directions combining to push more attention to time (e.g., Mohammed et al., 2009; Shipp & Fried, in press) and process dynamics in organizational systems (Cronin et al., 2011; DeShon, 2012; Kozlowski & Chao, 2012b; Kozlowski et al., 2013; Weinhardt & Vancouver, 2012; this special issue). At all system levels – micro, meso, and macro – dynamics are the next frontier. Team processes – at the juncture of macro contexts that shape emergence and the micro origins dynamic interaction – are the "sweet spot" for theory and research to advance this frontier.

Recommendations for Progress

Assuming that you accept this call to engage in theory building and research on dynamic processes in organizations, with a particular focus on teams, what can you do to advance this research direction? In addition to the actionable suggestions and examples I highlighted in the paper, I close with a six core recommendations for energizing this effort highlighted in Table 1.

First, *theory should explicitly incorporate a conceptual consideration of multiple levels and time.* Multilevel theory has become mainstream in organizational research, but it is important to remember that time is a level too. "Even the most "bare bones" group situations entail a *minimum* of three levels: group (i.e., between group), individual (i.e., person within group), and time (i.e. within person over time). There are potentially other levels as well …. You may not be interested in all these levels, but they nonetheless merit consideration in your theorizing, research design, and measurement" (Kozlowski, 2012, p. 260). Even if multiple levels and time are not operationalized, their explicit conceptual consideration will – slowly but surely – begin to advance understanding. It is a necessary point of departure.

Second, *theory that incorporates processes, assumed or explicit, should clearly, concisely, and precisely specify process mechanisms*. This recommendation essentially means that *all* theories in organizational science need to be more explicit and precise in their specification of process phenomena. Everything, or virtually everything[11], we study is infused with process assumptions and / or implications. However, the theoretical mechanisms that account for dynamics, change, and variability in processes are rarely described with precision. It

[11] I am at a loss to think of any meaningful organizational system phenomenon that has no process aspect.

is perhaps premature and a bit extreme to suggest that theoretical process mechanisms ought to be mathematically specifiable, but that is a necessary and desirable target for advancing quantitative research that incorporates dynamic processes.

Third, *encourage, support, and value good descriptive research*. As I mentioned previously, the only way the field is going to make progress incorporating temporal sensitivity and process dynamics in theory and research, is for us to begin compiling knowledge – a research foundation – that provides essential descriptive information. We need to know the time scales over which different phenomena emerge, change, and vary. Different phenomena emerge, change, and vary at different rates. We need to know time scale variation in those rates across different contextual contingencies. We need to know those time scales so we can estimate the length of time for study design and to determine sampling rates. We need good quantitative descriptive research to compile this knowledge. The second recommendation is less critical for qualitative researchers; their focus is on deep and rich description. However, detailed and precise qualitative descriptions could be extremely valuable for characterizing time scales, change rates, and variance in phenomena to help guide specification.

Fourth, *(seriously) appreciate the limits of cross-sectional designs and static assessments of process constructs*. The limitations of cross-sectional designs are well-established and well known, yet they continue to dominate our research. Obviously, the problem is not that investigators do not understand or know about the limitations, it is that longitudinal designs – and for process dynamics, intensive longitudinal designs – are more resource intensive, difficult, and risky. Nonetheless, moving beyond simple research designs is necessary to advance organizational science.

Fifth, *supplement traditional questionnaire-based measurement with alternative assessment tools*. I have argued in this paper that one of the primary limiting factors in efforts to capture process dynamics is the dominance of questionnaire-based measurement in our research designs. Questionnaires are obtrusive; they interrupt the stream of behavior. They are subject to response biases; biases that are exacerbated by repeated measurements. And, they are time consuming; they are inherently limited for high frequency sampling rates. All these factors limit their utility for capturing process dynamics. I recognize that they are nonetheless essential for assessing psychological constructs (i.e., phenomena "in the head" that have to be inferred), so we need them. But, I also recognize that they are limited slices of behavior and there are many ways that they can be supplemented by assessments of manifest, observable behavioral acts or artifacts of behavior. The field has tended not to explore and exploit these alternative options. I think they are essential for probing the dynamics frontier.

Finally, *adapt, innovate, and create new designs and paradigms for conducting research on emergence and process dynamics*. Throughout this paper, I have provided a number of examples and suggestions for ways that investigators can adapt, extend, or emulate existing approaches; alternative tools for behavioral assessment that are geared toward longitudinal designs and high(er) frequency sampling rates; and promising new paradigms that couple the strengths of traditional research designs with the third scientific discipline of computational modeling. All these suggestions have promise and merit. However, I make no claim that my suggestions are a comprehensive and exhaustive closed set. There are other potentially valuable approaches that merit discovery, exploration, and exploitation as well. That means having a multidisciplinary orientation, which is another emerging frontier.

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Table 1. *Six Recommendations for Advancing Research on Team Process Dynamics*

1. Theory should explicitly incorporate a conceptual consideration of multiple levels and time.

2. Theory that incorporates processes, assumed or explicit, should clearly, concisely, and precisely specify process mechanisms – mathematically, logically, or functionally.

3. The field should encourage, support, and value good descriptive research.

4. The field should (seriously) appreciate the limits of cross-sectional designs and static assessments of process constructs.

5. Researchers should supplement traditional questionnaire-based measurement with alternative assessment tools.

6. Researchers should adapt, innovate, and create new designs and paradigms for conducting research on emergence and process dynamics.

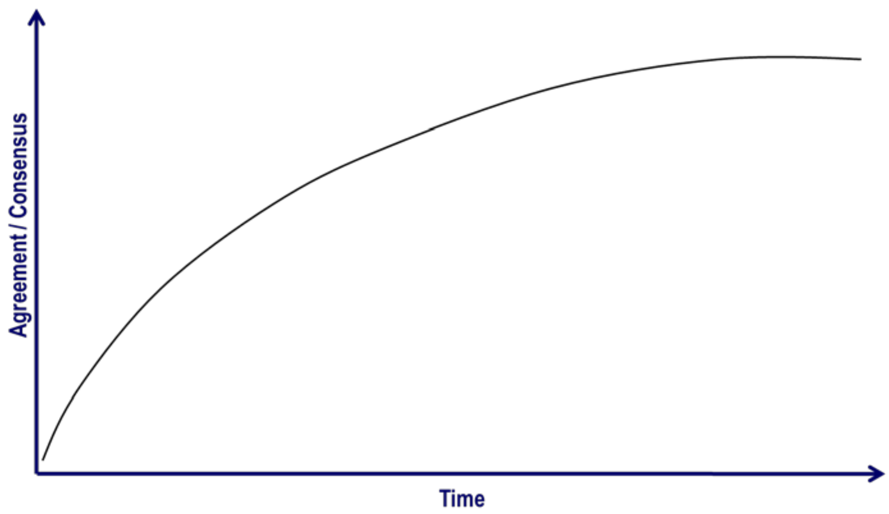

Figure 1a. Convergent linear emergence.

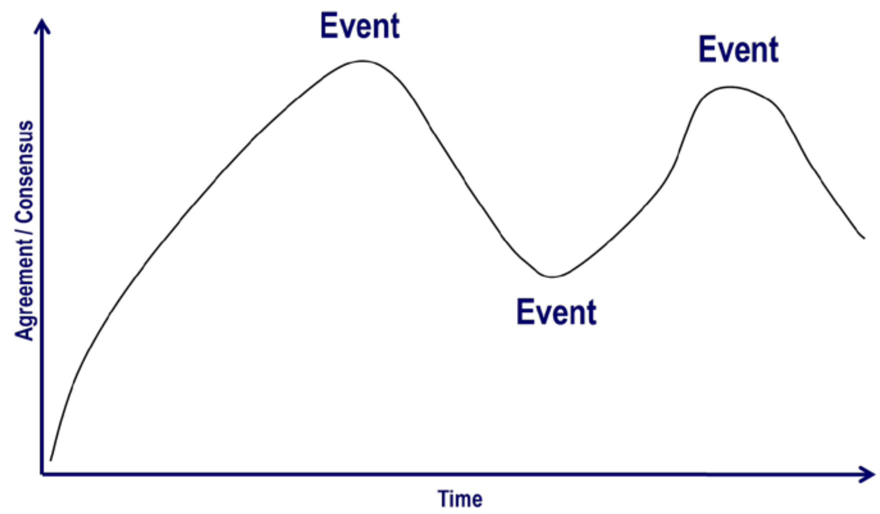

Figure 1b. Within team variability in emergence.

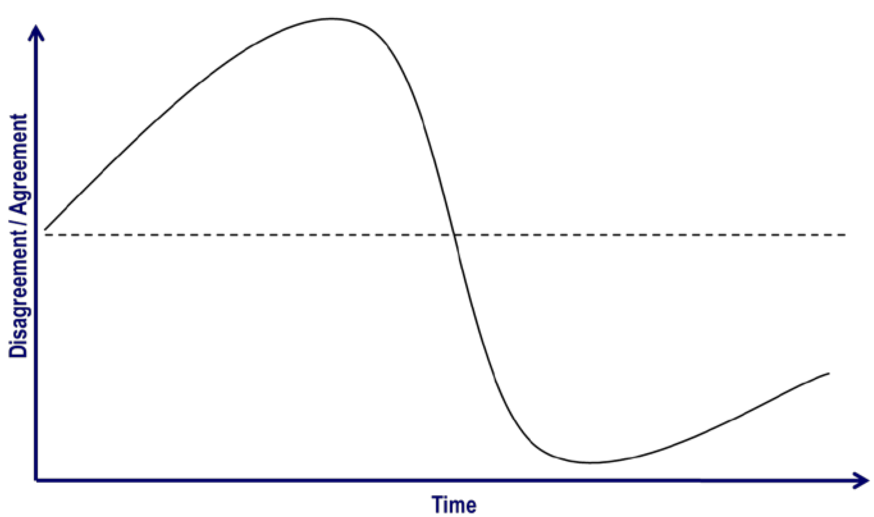

Figure 1c. Shift from convergent to divergent emergence.

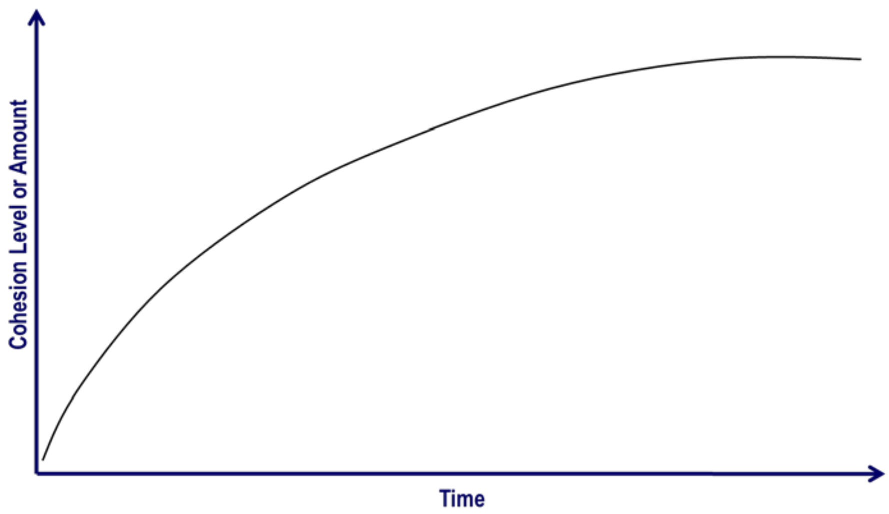

Figure 2a. Positive growth trajectory in the level of an emerged property.

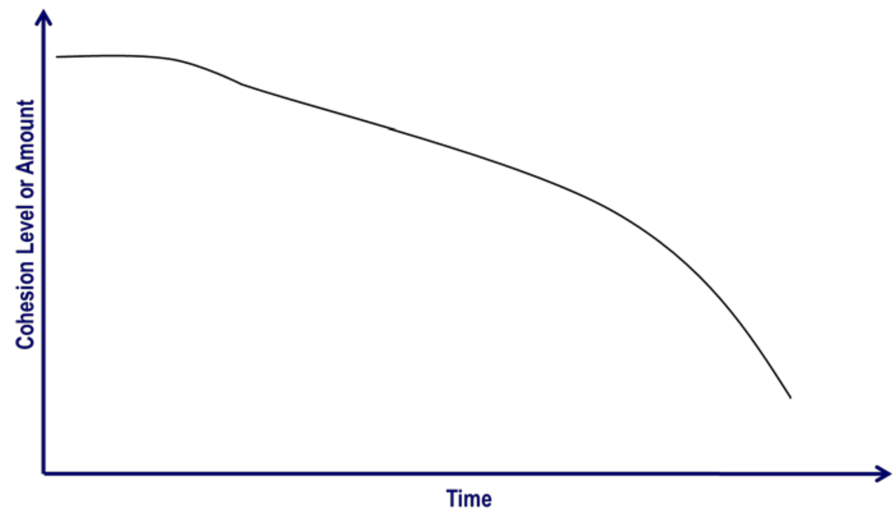

Figure 2b. Negative growth trajectory in the level of an emerged property.

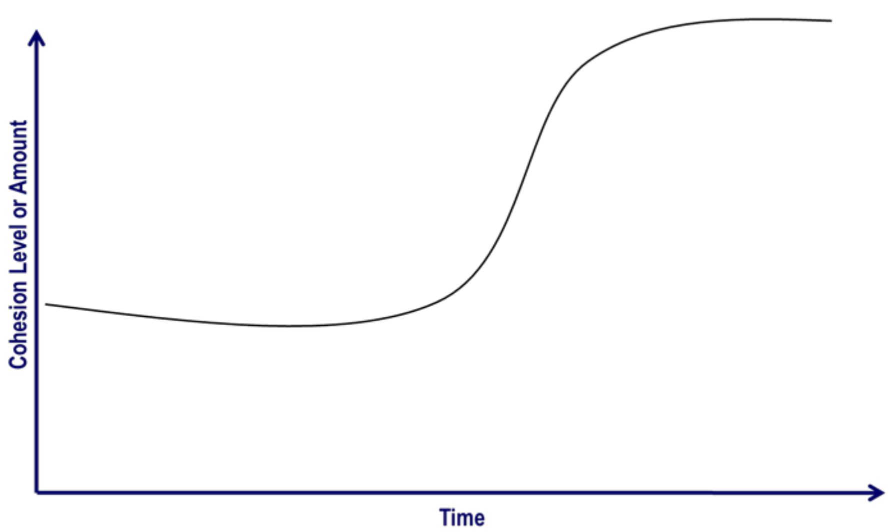

Figure 2c. Discontinuous shift in the level of an emerged property.

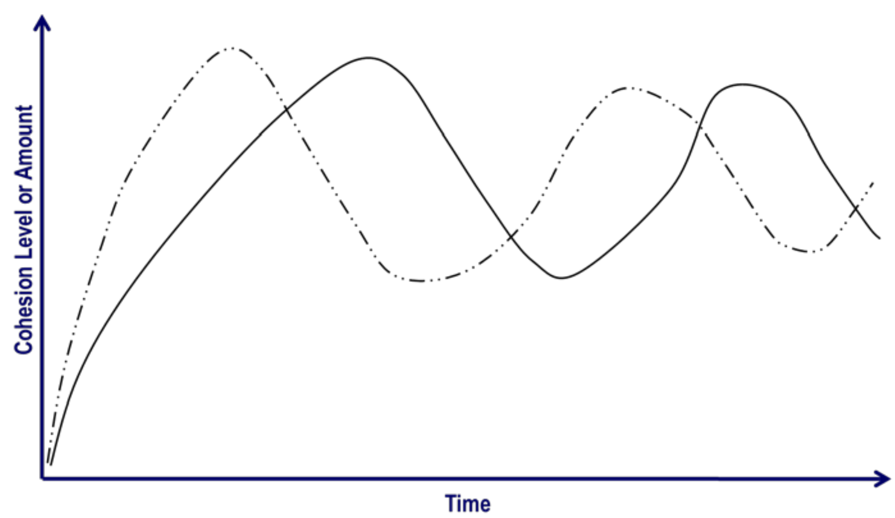

Figure 2d. Entrained cycles in the levels of emerged properties.