Team Dynamics:

Using "Big Data" to Advance the Science of Team Effectiveness

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Many influences have shaped the nature of organizational science during the transition from the 20th to the 21st century, but arguably two influences have been significantly transformative (Kozlowski, 2012). First, groups and teams research migrated from their long time home in social psychology to settle into their new location in organizational psychology and behavior (OPB). Indeed, Levine and Moreland (1990, p. 620) concluded famously 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." Team research in OPB exploded during the 1990's and 2000's (Kozlowski & Bell, 2013). Second, the heightened interest focused on team effectiveness coincided serendipitously with the migration of multilevel theory from the fringes of organizational science to become a core focus of mainstream OPB research. These two influences have revolutionized the field with respect to theory (incorporating multiple levels), research methods (resolving construct – measurement – and data alignment across levels), and analytics (capturing the interplay of effects across levels). But, the revolution has also been substantially limited by the absence of one critical focus. That focus goes by many names, but it is in essence attention to processes, their dynamics over time, and their emergence as higher level phenomena (Cronin, Weingart, & Todorova, 2011; Kozlowski & Chao, 2012). The next frontier for the science of team effectiveness, and OPB more generally, is to incorporate process dynamics at the core of our theories and research (Kozlowski, in press). This will necessitate another revolutionary advance … and this one will be energized by the advent of "big data."

As other chapters in this book and scholars have opined, big data in the form of digital traces (e.g., email, web surfing, blogging, social media networks, financial transactions, location services, etc.), video surveillance (e.g., while shopping, working, traveling, etc.), and other data traces that people generate during the interactions that comprise daily life in the modern world offers the promise of a *computational social science* (Lazar et al., 2009). The ability to pull together large pools of disparate data that capture human interactions and exchanges, identify meaningful patterns, and use them to predict important outcomes has the potential to radically transform the way we live our lives … and how we conduct science.

The potential capabilities and benefits are substantial, so there is a vigorous push to advance computational techniques to collect, integrate, and archive big data and develop statistical methods to explore, analyze, and extract meaning from it.[1] These efforts bring big challenges too. To draw meaningful inductive inferences, the data have to be representative and as complete as possible. Techniques for cleaning, integrating, and aligning such data sets are in their infancy, so the effort is laborious and fraught with problems.[2] Our research is more focused. Rather than striving to collect 'everything about everybody all of the time' (e.g., Google, the National Security Agency [NSA]), we have a middle-range focus on particular contexts (i.e., medicine, military, spaceflight), levels (i.e., individual, team, team networks), and time frames (i.e., minutes, months, years). These constraints or boundaries that we place around the phenomena of interest targets a middle range that allow us to capture 'everything about somebody some of the time,' thereby harnessing the promise of big data, but in a targeted way.

We study the dynamics of team processes and how team-level phenomena emerge over time from the interactions and exchanges among team members. We examine behavioral processes for emergency medical teams by video recording and coding team processes in high-fidelity patient simulation. We examine the dynamics of team learning and knowledge emergence in teams with distributed expertise that emulate a wide range of decision tasks used by the military and organizations. This research couples computational modeling (i.e., agent-based simulation) with a human team simulation. Finally, we study the dynamics of team

[1] http://www.nsf.gov/pubs/2014/nsf14543/nsf14543.pdf (accessed 21 August 2014).
[2] http://fortune.com/2014/06/30/big-data-dirty-problem/; http://www.nytimes.com/2014/08/18/technology/for-big-data-scientists-hurdle-to-insights-is-janitor-work.html?_r=0 (accessed 21 August 2014).

cohesion and collaboration in a range of spaceflight analog environments that include teams in the Antarctic (i.e., summer and winter-over deployments) and teams working in a range of National Aeronautic and Space Administration (NASA) mission simulations (e.g., transit, surface exploration). To provide some perspective, the data generated by these projects range – on the smaller end – from approximately 10 to 20 thousand data points per study for medical teams to – on the higher end – 20 to 500 million data points per study for the computational modeling and human team simulation, respectively, and to 250 to 750 million data points per team for one study for the NASA research. The teams are small, but the data generated are quite big! There are useful lessons to be learned across the projects that are useful for other investigators contemplating big data that we think merit sharing.

The chapter is organized as follows. First, we will discuss the long-standing treatment of team processes as static constructs rather than as dynamic processes per se. They are clearly treated as dynamic theoretically, but the treatment in research is overwhelmingly static. We suggest that this static treatment is largely due to limitations inherent in research design preferences and practices (i.e., limited view of dynamics, over-reliance on retrospective self-reports, and use of cross-sectional designs). Second, we will highlight research design issues that need to be considered in any effort to directly observe, assess, and capture teamwork process dynamics. The promise of big data is on the use of induction in a discovery mode, but we see important roles for coupling deduction and induction. Big data techniques are predicated on the use of classification and pattern recognition analytics to draw inductive inferences from an incomprehensible mass of linked data, but the quality of inference is ultimately determined by the quality of the data. One still has to know what data one needs to collect, why it will be useful, and how to examine it – so it is useful to have a strategy to guide research design. Third, we will explain how researchers can directly assess and capture team process dynamics using illustrations from three ongoing projects. Here, we will discuss the research design considerations by grounding them in the research illustrations, focusing on targeting the research design, and aligning measurement and data analytics. Finally, we will offer some concluding thoughts about the role of big data in advancing the scientific frontier with respect to dynamic phenomena.

Team Processes:

Emergent and Dynamic Phenomena or Static Constructs?

Overview

It is interesting to note that early interest in social psychology that centered on group or team[3] interaction processes was very much focused on the dynamic aspects of interpersonal communication and exchange processes. This interest is readily apparent, for example, in Lewin's Field Theory (Lewin, 1951) and Bales' Interaction Process Analysis (Bales, 1950). Indeed, the later development of the System for the Multiple Level Observation of Groups (SYMLOG; Bales & Cohen, 1979) incorporated a method for recording individual behavioral acts in sequence as they occurred during group interactions. McGrath (1964), of course, is also well known for his interest in the temporal aspects of team interactions as evidenced in his work on Group Interaction and Performance (1984) and, later, Time, Interaction, and Performance (1991). Even with the shift in the locus of team research from social psychology to OPB, theorists are in near universal agreement that team processes are dynamic phenomena (e.g., Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski, Gully, McHugh, Salas, & Cannon-Bowers, 1996; Kozlowski, Gully, Nason, & Smith, 1999; Kozlowski & Ilgen, 2006; Marks, Mathieu, & Zaccaro, 2001; Mathieu, Maynard, Rapp, & Gilson, 2008; McGrath, Arrow, & Berdahl, 2000; Salas, Stagl, & Burke, 2004) that are shaped by team inputs and influence team performance. Team performance, in turn, has reciprocal, cyclical influences back to inputs and / or processes. Team processes are viewed overwhelmingly as dynamic, at least on the theory side they are.

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[3] Although some scholars draw a sharp distinction between groups and teams as social units, we do not do so in this chapter and treat the units as equivalent for purposes of our discussion.

Unfortunately, they are not generally researched that way once investigators have to translate theory about dynamics into data. A review by Cronin et al. (2011) noted that the evident theoretical interest in team dynamics, rise of multilevel theory and methods, and advent of statistical tools for modeling time dependence and recursion should have "… invigorated the study of group dynamics; but did they? Regrettably, they did not…. dynamics are still largely missing from the study of groups" (pp. 572-573). Why? There are many potential influences (Cronin et al., 2011; Kozlowski, in press), but three in particular stand out. One is the apparent preference for "chain-like unidirectional cause – effect relationships" (McGrath et al., 2000, p. 97) that characterizes much team effectiveness research. A consideration of process dynamics necessitates a much more complex conceptualization of team phenomena. A second is the practice of treating dynamic processes as static constructs. In their review of the team effectiveness literature, Kozlowski and Bell (2003) observed that the static nature of team process research "… is due in large part to the assumed causal linkage inherent in the IPO heuristic, and the way that process is represented—by a box" (p. 346). This limitation is largely attributed to the way most team processes are assessed using dominant research practices (Kozlowski, in press; Kozlowski & Chao, 2012): as retrospective self-reports to a series of items tapping emergent constructs or what Marks et al. (2001) characterize as "emergent states." A third is the dominance of cross-sectional research designs in OPB. "Although cross-sectional designs are clearly more efficient, they by necessity can only treat temporally relevant phenomena like "team processes" as a box—a static representation of the essence by which teams create collective products. Longitudinal designs, though less efficient, will be far more revealing of the team phenomenon under investigation" (Kozlowski & Bell, 2003, p. 364).

Research Design Principles and Challenges

Develop a Targeted Research Design

One key promise of big data is the potential to use it as a fundamental tool for scientific discovery, particularly with respect to understanding complex, adaptive systems. "Fueled by cheap sensors and high throughput technologies, the data explosion that we witness today, from social media to cell biology, is offering unparalleled opportunities to document the inner workings of many complex systems" (Barabási, 2012, pp. 14-15). Drawing meaningful inductive inferences requires complete, inclusive, and expansive data. That's a challenge. And, although that is a challenge worthy of pursuit, we have deliberately focused our efforts on team process dynamics in particular organizational and work environments. Thus, we deliberately constrain context, level, and temporal focus.

Our team process focus is carefully targeted. We focus on observational indicators, core process mechanisms, and emergent constructs that are well supported by substantive evidence. This ensures that our research examines primary team processes, rather than those that may be novel or intriguing but are superfluous. For process dynamics, we examine core interaction events and associated behavioral, physiological, and / or psychological indicators. For emergence, we examine core micro-process mechanisms that drive interaction patterns and which ultimately yield the manifestation of team phenomena. For example, our research on medical teams is targeted on team process behaviors consistent with the Marks et al. (2001) typology (Grand, Pearce, Rench, Fernandez, Chao, & Kozlowski, 2013). Research on teams operating in isolated, confined, and extreme (ICE) environments for NASA examines emergent constructs and team process dynamics based on Kozlowski and Ilgen (2006), who were guided by findings from meta-analyses and promising research results. And, research on knowledge emergence focuses on core learning and sharing process mechanisms (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013, in press) that underlie team knowledge building. Parsimony is a useful principle to apply so that the data are directly germane to the substantive issue of interest. Our data are big, but less sifting is required.

Consider the Interplay of Deduction and Induction

Our operative approach is primarily deductive, but there is also an important role for inductive exploration to play. For example, our projects are all theory-driven and, thus, deductive in orientation. However, the team process data are distinctly different across the research settings. Considered broadly, the diverse data will begin to provide a basic descriptive foundation for describing / documenting team process dynamics under different contextual constraints and across different time frames (hours to days to months to years). Indeed, for one project, that descriptive aspect is essential so the research can document to what extent team processes vary and how much they do so. Big data will be important for establishing normative profiles of team evolution and long term functioning that will be used as benchmarks to assess new teams. Such data will also have a role to play in inductive exploration. Extant theory provides some notions about how individual and team process interactions may have lagged and cyclical influences on team performance, but it is fair to say that theory on team dynamics is substantially underdeveloped. Thus, big data will also be valuable for exploratory research to identify synchronous (i.e., conflict today relates to lower cohesion today), time-lagged (i.e., lower cohesion today relates to lower performance tomorrow) and reciprocal (i.e., lower performance relates to future cohesion and subsequent performance) relationships that can be used to aid theory building. As we will discuss, some of the tools, namely computational modeling and agent-based simulation, are explicitly designed to enable virtual experimentation in just such an exploratory role. Inductive inference and theory building then helps to fine-tune research design, measurement, and analysis. So, there is the potential for a very useful interplay between pure deduction and pure induction. Our projects are sensitive to this interplay between both modes of knowledge development.

Align Research Design with the Process Dynamics of Interest

At a fundamental level, a research focus on process dynamics means that the data collection design must go beyond the routine use of cross-sectional, self-reported, survey designs. Obviously, the cross-sectional aspect of many studies precludes any potential of capturing team process dynamics. So, that is out. On the other hand, it is often the case that self-reports are a primary, and sometimes perhaps the only way (i.e., reporting internal psychological states), to assess certain phenomena. So, there is a role for self-reported data, but it is desirable to supplement them with multi-source reports, other types of observations, and / or objective data. Moreover, as we discuss below, other considerations such as the desired resolution for capturing process dynamics (i.e., how frequently the phenomenon is assessed) will quickly constrain the utility of self-reported survey methods as the degree of desired resolution increases.

A well-aligned middle-range research design will have a clearly defined, bounded context and an overall time-frame that enables the observation of theoretically meaningful periods of teamwork interaction processes relevant to team effectiveness. Within that overall research time-frame, the design needs to incorporate assessments of core team processes at a frequency commensurate with the relevant rates of change needed to capture the micro-mechanisms of emergence, the emergence of team constructs, and / or their fluctuation over time and influences on other team phenomena (Kozlowski, in press). This means that some “tuning” is required with respect to the nature of measurement (i.e., by what modality team processes are assessed) and the frequency of measurement (i.e., how often the phenomenon is sampled).

As with most research design decisions, tradeoffs and challenges have to be balanced. That is the primary reason why we discuss three different projects. Each one illustrates different tradeoffs; across the projects, there is an overall balance. For example, one project uses video and audio recording, so (in theory) it has a very high (i.e., essentially continuous) recording rate. However, such raw observational data by necessity have to be coded and the methodology of the codes sets the sampling frequency and the degree of resolution for capturing team process dynamics. Another project uses Experience Sampling Methods (ESM) to capture relatively short sets of perceptual responses. We noted previously that one of the contributing factors to the treatment of processes as statics is the heavy reliance on the use of retrospective self-reports to assess team processes. ESM overcomes that limitation because the perceptions are sampled closer in time to actual experience and at rates much higher than one-shot surveys (Beal, in press). However, there are limits to how much you can ask, how often you can ask it, and for how long you can maintain compliance; so there are tradeoffs. We also use a novel technology – a wearable sensor package – that captures multiple data streams at very high sampling frequencies (i.e., essentially continuous) in real time. Here the challenge is fusing the copious multimodal data into a meaningful inference about the individual, dyadic, and team interaction quality; again, there are tradeoffs. The guiding principle is to sample at the highest frequency possible with the least degree of obtrusiveness, given what your resources and technology will enable (Kozlowski, in press).

Research Illustrations: Capturing the Dynamics of Team Processes

Overview

The purpose of this section is to provide a series of illustrations using our ongoing research projects as grounded exemplars to demonstrate how targeted individual and team process dynamics can be successfully investigated using rigorous quantitative methods and sophisticated analyses. The projects we discuss include research on:

- emergency medical teams in which the focus is on shaping team behavioral processes and linking them to team effectiveness;
- teams in isolated, confined, and extreme (ICE) environments that serve as “analogs” for space flight crews, in which the focus is on the dynamics of cohesion and collaboration and how those dynamics influence the psycho-social health of the team; and
- decision-making teams in which the focus is on the process dynamics of team knowledge emergence (i.e., how team members acquire problem-relevant knowledge and share it such that it manifests as a collective property) that can be applied to problem solving.

Each project is focused on a different type of team context, substantive focus, and targeted type of process dynamics. Thus, although not exhaustive, as a set they provide a good range of exemplars to illustrate how the theoretical foci regarding process dynamics can be instantiated in a research design that addresses the issues discussed previously: (a) targeting design to guide the collection of “big data,” (b) balancing deduction and induction, and (c) achieving alignment among the dynamic process of interest, sampling frequency, and analysis.

Team Behavioral Processes

Research focus and context. Emergency medical teams are at the “pointy end of the stick” in hospital emergency departments. When a person suffers a catastrophic injury, they are whisked away as quickly as possible (under ideal conditions) to the nearest emergency department. During the journey, emergency medical technicians compile whatever information is available regarding the circumstances of the injury and the patient’s vital signs. Upon arrival, the appropriate medical team is quickly assembled (whomever is on call) and presented with the available information on the status of the patient. Their task is to stabilize the deteriorating condition of the patient as quickly as possible, so the patient can be passed-off to the intensive care unit or appropriate interventional unit (e.g., operating room). The capabilities of such teams to quickly assess the situation, diagnose a course of action, and coordinate their expertise are key precursors of the clinical outcomes for the patient. These capabilities constitute the team behavioral processes of interest.

Targeted design. Studying emergency medical teams *in situ* is not impossible (e.g., Klein, Ziegert, Knight & Xiao, 2007), but it is very difficult. Because the project is focused on training intervention design and assessment, it is necessary to craft a research platform that is standardized and replicable. Hence, this research uses high-fidelity simulation to create synthetic experiences. It is conducted using a medical suite equipped with a high-fidelity, programmable, synthetic manikin that is capable of emulating a range of human disease states and associated physiological responses (see Figure 1). High fidelity patient simulators are in wide-spread use throughout the United States for medical education. Often, however, they are used to deliver an “experience” rather than training per se. That is, participants are presented with a realistic resuscitation scenario, the team performs, and performance is video and audio recorded. Then, the instructor leads an after action review using the video to highlight aspects of good and poor performance, offering process feedback, and providing lessons learned for the students. The experience is no doubt instructive, but the knowledge and skills acquired are not systematic so it is not training. Moreover, the knowledge and skills are rarely assessed, so what is acquired is essentially unknown.

Our use of this problem context and research setting necessitated the creation of a methodological infrastructure in the form of scenario design, measurement development, and validation so the simulator could be harnessed for systematic investigation of team processes. As noted previously, the capabilities of emergency medical teams to quickly assess the patient, diagnose a course of action, and coordinate expertise influence patient outcomes. Conceptually, these capabilities conform to a Planning – Action – Reflection phase structure, with specific team process behaviors relevant in each phase (see Figure 2). This conceptual structure represents an integration of the team regulation cycle (Kozlowski et al., 1996, 1999) and team task episode (Marks, Mathieu, & Zaccaro, 2001) models (Fernandez, Kozlowski, Shapiro & Salas, 2008). Team process behaviors and their dynamics across phase shifts are the focus of our research.

The development of this infrastructure is discussed in detail elsewhere (Grand, Pearce, Rench, Chao, Fernandez & Kozlowski, 2013). Here we highlight the key steps in brief. First, we developed representative, realistic patient resuscitation scenarios – content validated by SMEs – that were designed to provide a backdrop within which targeted team process behaviors could be exhibited. As shown in Figure 2a, a scenario comprises a series of "events" that drive a planning – action – reflection phase structure (Fernandez et al., 2008). Resuscitation scenarios generally fall within a 20 to 30 minute overall time window, with specific events (e.g., intubation, cardiac arrest) taking approximately 5 to 10 minutes each. Second, using the Marks et al. (2001) behavioral process taxonomy, we mapped specific behavioral indicators for relevant team process dimensions – content validated by SMEs – onto the event structure of the scenarios. Third, a similar process was followed to develop behavioral (observed) and objective (manikin metrics) of clinical care quality that were also validated by SMEs. Finally, the overall system was empirically validated (Fernandez, Pearce, Grand, Rench, Jones, Chao, & Kozlowski, 2013).

This research provides a lot of targeted data; on the order of 10 to 20 thousand data points per study. The video and audio are recorded in high definition, so the raw data in absolute file size are substantial. Coding of the video, which uses independent coders for the team processes and performance outcomes, comprise hundreds of behavioral indicators of team processes and team performance for a given team across a scenario. Add multiple teams and multiple scenarios, and you have an extensive data set for capturing and exploring team process dynamics that are precisely focused.

Deduction – Induction. This research is heavily oriented toward deduction. As shown in Figure 2, research design is driven by contemporary team effectiveness theory that conceptualizes team processes as dynamic across a phased structure encompassing a series of IPO "cycles" (Fernandez et al., 2008; Kozlowski et al., 1996) or "episodes" (Marks et al., 2001). Team process measurement is consistent with the Marks et al. (2001) taxonomy. The research is focused on developing targeted interventions that shape the quality of team behavioral processes. For example, we have developed and evaluated a short computer-based training intervention designed to improve team processes (Fernandez et al., 2013). Current research is developing a team leader training intervention that also targets team process improvement. A primary focus of our work is on science translation; that is, applying theory and research findings from OPB to the medical team context, so the primary emphasis on deduction is appropriate.

Nonetheless, the research platform can be used as a very rich source of information for inductive research. For example, one investigator is researching team leadership behaviors. This work necessitates an interplay between induction to develop appropriate dimensions and codes to capture leadership indicators, and deduction to evaluate a model examining the influence of leadership behaviors on team process behaviors and team effectiveness. Video and audio are very rich sources of big flexible data. In this case, the big data are obtained within a targeted context with an explicit theory and measurement structure to guide what to examine.

Alignment and analytics. High definition (HD) video is a continuous stream of behavioral action data, coupled with synchronous audio so that communication can also be extracted. Such data are very rich and highly flexible within their targeted time window and contextual constraints. However, in the absence of a targeted measurement system, aligned sampling frequency, and appropriate analytics; the data are just ‘movies.’ My novice investigators have recorded interesting team interactions, but then their big problem is: Now what? The research design has to be aligned.

A research focus on process dynamics necessitates careful consideration of temporal alignment. Thus, a key measurement principle is that one has to develop a targeted sampling of the data stream to populate the theory-driven team process dimensions. In our approach, this alignment is guided by the episodic event structure that is designed into the scenarios. For example, Figure 2b illustrates the event structure (Diagnosis, Intubation, and Arrest) and “time windows” for a scenario. Each event has an associated time window within which: (a) an event begins to unfold (e.g., initial indication of cardiac arrest – arrhythmia); (b) which should trigger planning behaviors (e.g., goal specification – resuscitation), action behaviors (e.g., coordination to execute the Advanced Cardiovascular Life Support algorithm of drug administration and defibrillation), and then reflection behaviors (e.g., sinus rhythm is restored; feedback – “good job” or “we should have accomplished that more quickly); at which point the event time window has closed and the team shifts back to stabilizing the patient or another event begins to unfold.

Specific behaviors are mapped to the event structure to index the team process dimensions. Depending on the research focus, behaviors can be aligned to the temporal structure of the unfolding event (within event), aggregated to the event level (within scenario), or aggregated to the scenario level (across scenario and / or between team).

An event structure allows precision in temporal alignment because the events set the tempo for the unfolding of team process behaviors. The key lesson is that the sampling frequency of the phenomena has to be commensurate with the rate of change (i.e., the dynamic frequency) that one is trying to capture. If the sampling rate is misaligned (i.e., too slow) then meaning micro-dynamics in the phenomena of interest will not be captured and cannot be recovered. On the other hand, sampling at high frequency has costs (e.g., many more surveys, more specific coding, etc.). As a general rule-of-thumb, we advocate sampling at the highest frequency possible given resource constraints and participant engagement. High frequency data can always be sampled or aggregated, but missed observations are simply gone.

As noted previously, recorded video and audio provide highly flexible raw data. Codes extracted from the raw data can be very precisely time aligned or aggregated upwards to capture meaningful team process clusters. Behaviors can be sampled at the team level, or the coding can be linked to individual team members to track process linkages as a dynamic network of actions. It can be resampled and recoded to supplement existing codes or to focus on entirely different process phenomena (within the context). Thus, researchers can increase or decrease the behavioral units under observation and the time frequency to hone in on exactly what they want to assess. Unfortunately, this approach is labor intensive. One has to have a rigorous measurement framework or you will not be able to extract reliable and meaningful codes (Grand et al., 2013).

Analytics, of course, need to fit the research question. The research we are conducting – as translational science – is examining the effect of interventions on team processes and effectiveness. From an intervention evaluation perspective, we are simply interested in the effects of an intervention on enhancing team processes and team performance (e.g., Fernandez et al., 2013). However, such a focus does not get at process dynamics per se.

The data could also be examined with a more sophisticated approach using structural equation modeling (SEM) that would better capture the temporal structure. For example, consider a design that incorporates a scenario, assessment of emergent process states (e.g., team mental model, efficacy, and cohesion), another scenario, and an assessment of effectiveness perceptions (e.g., viability, satisfaction). One could examine the influence of input factors (e.g., team experience, training) on team behavioral processes and performance; the effects of inputs, processes, and performance on subsequent emergent states, and the effects of the emergent states (incorporating the process and performance lags) on subsequent processes, performance, and viability outcomes. This is merely one possible model, as SEM is quite flexible (e.g., one could endeavor to unpack the event structure as well). This approach gets us closer to dynamics.

Alternatively, we might be interested in identifying the *patterns of team processes* that were most effective. Such an analysis could be applied at the scenario or event level. For example, Grand, Pearce, and Kozlowski (2013) used a regression-based pattern recognition analysis (Davison & Davenport, 2002) to identify profile patterns of team processes that covaried with the performance of effective teams across scenario events. The findings indicated that the pattern of team processes explained significant and substantial variance beyond that accounted for by the average level of team processes. Thus, beyond the amount of team process behavior exhibited, the particular configuration of processes was predictive of team effectiveness. This approach begins to capitalize on the promise of big data to unpack team processes.

Dynamics of Team Cohesion and Collaboration

Research focus and context. Someday, in the not too distant future, a team of astronauts will depart near earth orbit to embark on a journey to explore our solar system, including an inter-planetary expedition to Mars. What will such a mission be like? The composition of the crew and mission specifics have yet to be finalized, but ongoing planning allows some parameters to be reasonably estimated. For example, the Orion Multi-Purpose Crew Vehicle[4] will likely be the crew module (i.e., take-off, abort, re-entry) for deep space missions. The first test flight for Orion is slated for late 2014. Launch will be provided by a new Space Launch System. And, for exploration, Orion will be mated with a new Service Module that will serve as the habitat for the crew. For a mission to Mars, the crew compliment is likely to be six astronauts. The habitable volume in the Orion and Service Module configuration will be quite tight. There will be high propinquity and very little privacy, creating some degree of interpersonal stress. The crew will be together for a very long time. Beyond the years of training, mission duration is likely to be 32 months at a minimum. Transit is estimated at 8.5 months each for outbound and return. Time for surface exploration is dictated by a planetary alignment that is needed for the return flight. So, the exploration aspect of the mission cannot be shorter and any increase means a much longer overall mission. Communications with mission control (and family and friends) will be difficult (e.g., roughly 40 minutes – 20 minutes each way – to have a two-way exchange at maximum distance with Mars). Thus, one can anticipate an astronaut team being subjected to a mission characterized by isolation, confinement, and extreme conditions for a very lengthy time. It is a very immersive experience. What can be done to help the team maintain its effectiveness under these challenging conditions?

Several lines of systematic research, large scale literature reviews, and meta-analytic summaries have firmly established that team processes, as key indicators of psycho-social team health, are critical contributors to team effectiveness (Ilgen et al., 2005; Kozlowski & Bell, 2003, 2013; Kozlowski & Ilgen, 2006; Mathieu et al., 2008). Disruptions to teamwork, due to conflict, low cohesion, or poor collaboration, have the potential to threaten team functioning under the ICE conditions that can be anticipated for long duration space missions. These

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[4] http://www.nasa.gov/exploration/systems/mpcv/#.U_tvKmM0-XM (accessed 25 August 2014).

difficult operating environments are further challenged by high team autonomy given time lagged communications with mission control. For high reliability teams, a disruption in good teamwork, especially when team coordination is critical, can have disastrous consequences (Weick, Sutcliffe, & Obstfeld, 1999). Thus, the capability for NASA to measure, monitor, and maintain good teamwork interactions for flight crews and mission control teams is essential.

One of the key challenges of conducting human research for NASA is that the population of astronauts (and other relevant mission personnel) is not very large. Moreover, opportunities to study space teams *in situ* are extremely limited. Thus, NASA has identified a set of “analog” environments that emulate aspects of space missions, their extremity, and / or personnel that are used as primary research contexts for studying team interaction processes relevant to space flight crews who will one day embark on long duration missions outside of near Earth orbit (see Figure 3). The analogs of interest – in rough order of realism – include the NASA Extreme Environment Mission Operations (NEEMO; an undersea habitat), Human Exploration Research Analog (HERA; a transit mission simulation), the Hawai’i Space Exploration Analog and Simulation (HI-SEAS; a Mars surface exploration simulation), and real ICE teams that conduct scientific research (summer deployments) or winter-over in the Antarctic.[5]

Targeted design. The targeted “big data” aspects of the project have two primary foci. First, we are collaborating with an engineering team to develop an unobtrusive team interaction assessment technology. Essentially, it is a sensor platform – a wearable social interaction “badge” – that captures dynamic, real-time multimodal data streams (i.e., physical, physiological, and behavioral) data capturing team member and teamwork interactions. This technology generates copious data. Second, we are using experience sampling methods (ESM) to collect data designed to benchmark long-term team functioning in NASA and ICE analogs. Depending on the analog, we use the badges and / or ESM to assess team process dynamics

[5] The International Space Station (ISS) is the most realistic analog for long duration space missions, but access for team process data collection is, as one might expect, very limited.

over a variety of mission durations, ranging from one week up to one year. Across all the research settings, the teams are small – typically 4 to 8 people – and the sample is often comprised of only one, and occasionally two or three, teams. In essence, the data collections assess the within-team dynamics and ecology of single teams. Hence, much of our research focus is on individual dynamics and interactions among team members. Although the teams are small, the data can be quite big. Next, we discuss each type of data collection – badge and ESM.

The wearable sensor system (Baard et al., 2012a, 2012b; Quwaider & Biswas, 2010) provides a continuous feed of multimodal data to capture teamwork interaction and process dynamics. The concept of the system is very similar to the sociometric badges developed by the MIT Media Lab.[6] However, the badge under development streams continuous multimodal data that can be distributed to other devices (i.e., smart phone, tablet, and / or computer) for viewing in real-time, whereas the Sociometric Solutions badge stores interaction data onboard for later upload and processing.[7] The sensor system consists of a wearable badge, which contains the sensor array, and a receiver / server to record the data streams and to distribute it via a web interface. The sensor package is roughly the size of a smart phone, although the sensors could be sewn directly into clothing. The sensors monitor the intensity of physical movement, vocal intensity, heart rate, and face-time (interaction distance) with teammates who are also wearing sensors. Over time, one can identify the sequence, frequency, duration, and degree of arousal associated with patterns of interactions among team members. Structured team member interactions under highly controlled conditions have been used to validate the sensor data streams (Baard et al., 2012a, 2012b). Current research is evaluating the badges in a range of analog settings.

[6] http://hd.media.mit.edu/badges/publications.html (accessed 20 August 2014).
[7] http://www.sociometricsolutions.com/ (accessed 20 August 2014).

As highlighted previously, although there is considerable research on the relationship between teamwork processes that reflect the quality of team member interactions, such as cohesion, conflict, and collaboration, most of the research is static. However, theory suggests that collaboration patterns and interaction quality vary over time as a team is assembled, undergoes developmental experiences, and works interactively together over lengthy time frames. It is a fact of life that team members have to manage work-related problems and the challenges of social friction. However, relatively little is known about such dynamics because the majority of team process research has been cross-sectional (Kozlowski & Ilgen, 2006).

As you might imagine, the sensors collect copious amount of data. For example, teams of 6 in the HI-SEAS simulation generate approximately 250, 500, and 750 million data points across 4, 8, and 12 month missions. Our use of the sensor technology for NASA is designed to develop protocols to infer the quality of team member interactions and, when anomalies are assessed (i.e., meaningful departures from normative functioning), to trigger counter-measures to recover and restore cohesiveness. These technologies, however, have broad applicability. For example, one could use badge data to examine the dynamic interactions among members of research and development teams to see what type of network ties and network structures yield the most knowledge creation and innovation (e.g., Olguin, Gloor, & Pentland, 2009; Olguin, Waber, Kim, Mohan, Ara, & Pentland, 2009).

We use ESM to collect benchmarking data for ICE teams in the Antarctic. These data are intended to set normative standards for expected variation in team functioning for long duration missions. Many science field teams deploy to the Antarctic to conduct scientific study during the Antarctic summer, when conditions – although still quite challenging – enable them to deploy to the ice. The teams we are studying spend six weeks camped in the field seeking samples. In addition, permanent stations are an important part of the science infrastructure in the Antarctic. Stations have to be staffed and maintained, even during the difficult Antarctic winter. Crews who winter-over spend roughly nine months, mostly confined to the station, doing their work with teammates. In both settings, team members provide daily ESM ratings to assess the nature of the work (e.g., mental and physical workload), a variety of team process states (e.g., cohesion, conflict), and outcomes (e.g., performance, satisfaction).

We are also collecting benchmark ESM data from crews in NASA analogs that simulate transit and exploration missions. We have collected ESM and badge data from 4-person crews during three HERA missions; this data collection is ongoing. In addition, we have collected ESM and badge data from a 5-person crew at HI-SEAS during a 4-month mission. Two additional missions for two 6-person crews are planned that will extend mission duration to 8 and 12 months. Finally, we collected one week of ESM and badge data from the crew of NEEMO mission 18, which consisted of an international team of four astronauts and two habitat technicians.

It should be noted that our research team is just one among many who are studying team phenomena in NASA analogs. Other investigators are focusing on physiological monitoring, video recording, and communication (audio to text) as data sources. The discussion that follows centers on the badge and ESM data, but this setting provides a real big data integration opportunity across all the different data modalities.

Deduction – Induction. One of the more interesting aspects of this project is the interplay between deduction and induction. For example, some of the mission simulations include workload and other manipulations (e.g., communication time lags) designed to stress team members. This is deductively oriented research in which we expect the stressors to influence the quality of team member interaction and exchange with effects on performance. But the research is also inductively oriented in two primary ways. First, our ESM data collections are building a descriptive research foundation of the longitudinal functioning of individuals and teams of different types, under different conditions, and across a range of durations. Although we have theoretically “inspired” notions about how shocks or disruptions to team members (e.g., bad weather, equipment failure, social conflict) may influence the variability of team processes and outcomes in the form of daily fluctuations, the data also enable exploratory analyses to identify time-lagged, reciprocal, and asymmetrical relationships. We are also examining different overall patterns of functioning that may be useful for classifying team profiles. Second, the badges stream a prodigious quantity of interaction data across several different sensing modalities. Again, although we have theoretically inspired ideas about how the data streams can be used to capture the quality of team interaction, it is also likely that such data contain non-linear patterns that do not conform to any current theory of individual and team interaction. Thus, one key aspect of developing the badge into a useful team regulation support system (i.e., assessment, diagnosis, and feedback), is the use of data mining techniques to quantify patterns across the sensor data streams that are predictive of individual and team process states and outcomes. For example, badge data can be coupled with frequent self-reports of affect (activation and valence) that can serve as criteria. As a simple example, one can create a 2 X 2 matrix of the orthogonal dimensions. Data mining tools (e.g., Weka[8], TDMiner[9]) can then be used to identify patterns among the data streams that classify the states of team members or teams into the 2 X 2 over given time frames (e.g., minutes, hours, days, etc.).

Alignment and analyses. As described by Beal (in press), ESM can be viewed as an umbrella term for a set of techniques (i.e., ecological momentary assessment, ambulatory assessment, everyday experience methods, and daily diary methods) that are all predicated on capturing experience *in situ* over meaningful time frames. They are intensive time series designs that enable an examination of research questions that are not amenable to investigation using conventional between subject research approaches. In that regard, they are idiographic in nature (i.e., within person), rather than nomothetic (i.e., between person). This raises issues regarding the generalization of findings about the dynamics of individuals to the broader population. However, looking across individuals in a common experience and across those

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[8] http://www.cs.waikato.ac.nz/ml/weka/index.html
[9] minchu.ee.iisc.ernet.in/new/people/faculty/.../TDMiner-User-Manual.doc

exposed to different experiences, and identifying clusters with similar patterns, represents a meaningful generalization target (Velicer & Molenaar, 2013).

Intensive longitudinal data at the person level enables an examination of process dynamics that are not amenable to traditional research designs (Iida, Shrout, Laurenceau, & Bolger, 2012). Primary foci include: (a) the average states of a person and how much variability the person exhibits over time; (b) the extent to which there is a systematic change in states over assessments, the nature of change (e.g., linear, quadratic, other), and whether the trajectories are similar or different between persons; and (c) identification of cyclical, reciprocal, and lagged relationships among factors (e.g., workload), states (e.g., conflict, cohesion), and outcomes (e.g., satisfaction, performance).

As mentioned previously, the research goals regarding process dynamics need to be aligned with assessment frequency. In other words, the rates of change for the phenomenon of interest should be commensurate with the sampling frequency (Kozlowski, in press). This isn't rocket science. If one assesses on a daily basis but the phenomenon changes more rapidly, then you are going to miss those micro dynamics. On the other hand, there are also pragmatic constraints such as how often you can ask respondents the same questions and expect to get meaningful answers (Beal, in press). One way we have tried to address this trade-off is to recognize that the different ICE settings are useful for providing different team process insights. Thus, sampling frequency is shaped by both the degree of desired resolution in the data and what can reasonably be accomplished given pragmatic constraints.

For example, our ESM assessments for the Antarctic teams are conducted on a daily basis. More frequent assessments would be desirable, but the participants involved are in real ICE experiences and that is not pragmatically feasible. However, it is also the case that the factors that are likely to play a role in dynamics (e.g., work stress, fatigue, sleep deprivation, bad weather, interpersonal conflict) are likely to align with a daily sample rate, with lagged effects that manifest one or two days later. We have two different longitudinal durations ranging from approximately 45 daily assessments to roughly 270 daily assessments.

In contrast, our ESM assessments in the mission simulations are more frequent, on the order of three times per day. This allows for a more fine-grained examination of process dynamics (albeit under simulated conditions). Here the durations span 21 assessments (7 days) to over 1000 (1 year). Thus, part of the analytic strategy is to look for clusters of similar within person patterns across different settings and durations (Velicer & Molenarr, 2013) as a means to generalize the findings of these largely ideographic methods. If we find patterns that are robust across settings and that manifest across different durations, there will be more confidence that such patterns (e.g., weekly cycles; Beal, in press) are likely to generalize.

Intensive time series data can be analyzed with a variety of approaches. According to Velicer and Molenarr (2013), the methodology most frequently used in psychology is a class of models labeled autoregressive integrated moving average models (ARIMA; Box & Jenkins, 1976;). In OPB, such data are most often analyzed using multilevel or random coefficient modeling (Beal, in press), although DeShon (2012) suggests that vector autoregressive (VAR) models may be more useful for unpacking the dynamics multiple time-series data. Consistent with Beal's (in press) advice, our general approach is to determine whether the targeted process states of interest are stable or exhibit trends, cycles, or lagged (autoregressive) effects. As this research is in progress, we have not conducted extensive analyses. However, based on the literature, we anticipate observing within day cycles (where the resolution allows it), daily trends, weekly cycles, and daily lags (Beal, in press).

For example, we collected daily ESM data from 26 participants who wintered-over in the Antarctic for durations that ranged from 9- to 15-months (Baard, Kermond, Pearce, Ayton, Chang, & Kozlowski, 2014). Participants rated their daily positive and negative mood, cohesion, conflict, conflict management, and performance. Overall, 2333 daily measures were completed by the participants. Using the random coefficient modeling, we found that there were reciprocal relationships between daily cohesion and the subsequent day's performance ratings and vice versa, such that prior cohesion was predictive of subsequent performance and prior performance was also predictive of subsequent cohesion, after controlling for the autoregressive effects. Cohesion and performance were self-reinforcing. Reciprocal relationships between positive mood and conflict were also observed, such that prior positive mood predicted lower subsequent conflict, and prior conflict predicted lower positive mood in the future, after controlling for the autoregressive effects. Asymmetrical relationships were also observed. In particular, prior positive mood predicted lower subsequent negative mood, but not the other way around. Conflict management was a positive predictor of subsequent cohesion, whereas prior cohesion was not a significant predictor of subsequent conflict management effectiveness.

Badge data constitute much more of a focus on micro dynamics. Indeed, this is where the small world of one team becomes a very large world of big data. Such data can be scaled (filtered, aggregated) in any number of ways, so it opens many interesting prospects for the investigation of team dynamics. We are interested in individual variability over time on the multimodal metrics, and those data (with appropriate filtering and aggregation) can be examined with the same types of analyses applied to ESM data. Moreover, the badges represent novel data that can be examined in novel ways. For example, work in clinical psychology is challenging the notion that psychopathic disorders (e.g., depression) are latent constructs represented by a set of manifest indicators (i.e., symptoms, diagnostic items). Instead, the disorder is conceptualized as a phenomenon that is a complex dynamic system of causally linked symptoms that self-reinforce (Borsboom & Cramer, 2013; Schmittmann, Cramer, Waldrop, Epskamp, Kievit, & Borsboom, 2011; Wichers, 2014). Data-based investigations of this conceptualization make use of network models and, again, intensive time series. This is an intriguing idea, because the concept of team cohesion, divorced from conventional survey assessment and aggregation, can also be considered a phenomenon that is a complex system of causally linked relations.

Consider, for example, a three-member team: Alpha, Bravo, and Charley. Alpha and Bravo have known each other for a long period of time and have many things in common. So, A and B are close socially. Alpha and Charley, however, have very similar educational backgrounds and expertise. So, A and C are close on taskwork. With this simple structure, one can easily imagine how patterns of interaction (i.e., frequency, duration), arousal (i.e., heart rate [HR], HR variability), and stress (i.e., vocal intensity modulation) could be indicative of a phenomenon called team cohesion. Moreover, it is not difficult to conceptualize how events that are external (i.e., work load and tempo, equipment failures) or internal (i.e., interpersonal conflict) would play out dynamically in the frequency and duration of dyadic interactions, the degree of arousal when in proximity of others, and in the nature of their communications. This is a simple example, but the point is to draw attention to the idea that the dynamic relations among the different manifest indicators are representative of the state of the phenomenon – team cohesion.

There are a variety of candidate analyses that can be applied to such data. A detailed treatment is beyond our remit. However, the network approach describe previously (Borsboom & Cramer, 2013) is one promising candidate. Another is the VAR model for handling multivariate time series data (DeShon, 2012). Besides description and forecasting, this approach is also useful for examining the causal impacts of “shocks” to specific variables in the time series and the effects of those shocks on the other variables in the system. Relational events analysis (REA; Butts, 2008), which is “a highly flexible framework for modeling actions within social settings which permits likelihood-based inference for behavioral mechanisms with complex dependence…. [and which can examine] base activity levels, recency, persistence, preferential attachment, transitive / cyclic interaction, and participation shifts with the relational event framework” (p. 155). And, of course, as part of an inductive – deductive interplay, such data are amenable to a range of machine learning and data mining techniques as a way to identify non-linear patterns arising from the multimodal data that are predictive of effective team functioning.

Team Knowledge Emergence

Research focus and context. A patient visits his or her general physician and complains of pain in the region of the lower back. The pain could be due to a variety of maladies, so the physician schedules a functional magnetic resonance imaging (fMRI) scan. The radiologist reads the fMRI scan and reports. The patient, in consultation with the physician, radiologist, and potentially a surgeon, consider the best course of action to manage the discomfort. Onboard a US Navy vessel, part of Combined Task Force 150 (a multinational coalition) that is off the Somali coast, messages are being received that report multiple possible sightings of Somali pirates. That information is being combined and coordinated by experts with data from aerial surveillance, radar, and underwater listening devices to decide where to vector the vessel's lone chopper to prevent a hijacking. In the control room of a nuclear power plant, alarms suddenly trip indicating a cooling problem in the reactor. The control room crew is under time pressure to identify the source of the problem and to take effective action to prevent the power plant from becoming another pejorative term like Three Mile Island, Chernobyl, or Fukushima.

Teams are often used – in medicine, the military, and industry – in mission-critical decision-making situations where professionals with distinctively different expertise have to pull together information about a specific problem, share their knowledge to develop a common understanding, and then apply it to decide where to allocate limited resources to resolve the problem, often under tight time pressure and with high consequences for errors of judgment. The same team decision processes are also common in business organizations, although usually the outcomes are less time pressured and consequential in terms of human life.

Drawing on the human factors literature, Fiore and colleagues (Fiore, Rosen, Smith-Jentsch, Salas, Letsky, & Warner, 2010) describe this form of team collaborative learning and decision making for uncertain, complex, and consequential problems as "macrocognition." However, this conceptualization of team learning as a collective process and teams as information processors who are subject to biases and sub-optimal decision making has deep roots in the psychological literature more broadly (e.g., Bell, Kozlowski, & Blawaith, 2012; De Dreu, Nijstad, & van Knippenberg, 2008; Hinsz, Tindale, & Vollrath, 1997; Stasser, 1999; Stasser & Titus, 1985).

Targeted design. This type of distributed team information acquisition and decision making has been widely studied. For example, there are literally thousands of research studies using the “hidden profile” paradigm (Stasser, 1999; Stasser & Titus, 1985) in which decision makers have access to common (shared) information but also unique (privately assessable) information that represents distinctive expertise. A robust finding in this research is that team members spend far more time discussing common information, and pay much less attention to unique information. Because the unique information is diagnostic for the optimal decision (the hidden profile), team decisions are typically sub-optimal. Also, because teams usually only engage in one decision in such research, there is no feedback and learning. Our interests in this area of inquiry were less focused on the distribution of common and unique information, and much more focused on issues relating to team dynamics that heretofore had received virtually no research attention. Those interests centered on how team-level knowledge emerged dynamically from individual learning processes, how it could be measured, and how it could be systematically examined as a longitudinal process.

The approach we developed is innovative in that it couples human research using a synthetic team task in a laboratory setting with “virtual experimentation” based on a computational model (CM) implemented in an agent-based simulation (ABS; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Kozlowski, Chao, Grand, Braun, & Kuljanin, in press). First, applying the principles of multilevel theory to the model of macrocognition (Fiore et al., 2010), we developed a set of metrics that could capture the dynamic patterns of team knowledge emergence (Kozlowski & Chao, 2012). Second, using the metrics as targeted outcomes to represent patterns of knowledge emergence, we developed a theoretical model of the learning and knowledge sharing mechanisms (Kozlowski et al., in press). This provided the basis for developing the CM of team knowledge emergence. A CM is a precise – mathematical or logic-based – model of a system that specifies how a dynamic system changes from one time point to the next. The core process mechanisms – the drivers of system dynamics – of the CM were individual learning and knowledge sharing linked to the knowledge emergence metrics. These mechanisms were then instantiated in an ABS. We used the ABS to conduct virtual experiments by manipulating factors that were presumed to influence the process mechanisms of learning and sharing, and observing the effects on the knowledge emergence metrics. That work provided insights regarding where and why teams developed bottlenecks in the knowledge emergence process. Third, in parallel with the CM / ABS development, we designed a synthetic team task that could be used for human experimentation. For example, in our ABS research the knowledge emergence metrics were used to identify problematic points where agents plateaued or became bottlenecked. We then used that knowledge to design interventions for human teams that mitigated the bottlenecks, thereby enabling intervention teams to out-perform control teams. Long term, the paradigm is designed to use the CM / ABS to conduct basic research. The CM / ABS can explore a meaningful theoretical space and identify interventions and / or process dynamics of interest. The agents do the heavy lifting. Human research, which is much more time and resource intensive, is then used to verify and validate interesting observations (Kozlowski et al., 2013, in press).

We have also embarked on a new research effort that will develop a more complex CM / ABS for studying formal and informal leadership mechanisms, team processes, and team effectiveness for multi-team systems. This new research effort will involve the development of a CM that emulates a broader range of team inputs (e.g., leadership, composition), process mechanisms (e.g., cognition, cohesion), and outcomes (e.g., performance); examines both within and between team interactions; and examines the effects of internal and external shocks on team adaptation and effectiveness. Modeling efforts of this sort generate massive, temporally sensitive data sets (i.e., approximately 22 million for the ABS).

Deduction – Induction. This research paradigm explicitly builds in a linkage between inductive and deductive research approaches. For example, our initial research using the CM / ABS allowed us to examine input factors that were expected to influence the process of team knowledge emergence. We manipulated the distribution of common to unique information, agent cognitive ability (i.e., learning rate parameter) and agent extroversion (i.e., sharing rate parameter). We manipulated these factors to get wide variance on the emergence metrics as a means to validate both the CM and the metrics. However, interesting effects that we observed on the patterns of knowledge emergence via the metrics were then used to guide the design of "embedded agents" that were programmed into the human team simulation. Based on the bottlenecks and other anomalies we observed in the agent teams, the embedded agents were triggered when team member behavior fit an anomaly profile. The embedded agents provided dynamic advice or feedback to help improve human information acquisition, knowledge sharing, and decision making (Chao, Kozlowski, Grand, Braun, Kuljanin, Pickhardt, & Mak, 2013). This was a process of inductive to deductive research.

A similar interplay using modeling is described in research by Kennedy and McComb (2014) who video recorded laboratory teams working on a problem-solving task. They coded communication patterns to identify transition – action phase shifts (Marks et al., 2001). They then conducted virtual experiments to compare (a) the observed lab (human) teams with (b) simulated (agent) teams that received simulated interventions intended to improve communication patterns and (c) simulated (agent) teams with optimal (based on a genetic algorithm) communication patterns. The findings from virtual experimentation were used to theorize about ways in which team communication patterns might be improved via interventions to enhance team effectiveness.

Alignment and analyses. This line of inquiry is really interesting because of its focus, scope, and ability to capture a wide range of process dynamics. The research design focus constitutes a well-defined, bounded context. It is a middle-range problem space that is highly generalizable to a wide range of teams and task contexts. Within that defined context, the amount of fine-grained behavioral data that is generated is astonishing. Moreover, it allows a "scaling" of the process focus that ranges from very precise micro-dynamics up to more molar, meso- and macro-level dynamics. Finally, the behavioral data are exceptionally precise. Some might view such a well-defined research setting as too limited. It is a small world, but one with an enormous set of opportunities for inductive theory-building and deductive theory-testing (Kozlowski et al., 2013, in press). It provides a test-bed for investigating the process mechanisms of emergence and team process dynamics across scales that encompass micro, meso, and macro levels.

Consider, for example, the primary process mechanisms of team knowledge emergence – information acquisition or learning and knowledge sharing – that are the focus of the CM and the synthetic task, CRONUS.[10] The task is designed to track each behavioral act for each team member. The onset, execution, and closure of each act are time stamped. Thus, the precise timing, duration, sequencing, tempo, and pattern of acts across team members as they endeavor to extract information from the problem space and convey it to their teammates is coded in the data[11]. In a typical experiment, CRONUS generates approximately 500 million data points that capture the micro-dynamics of team knowledge emergence. The CM also tracks each act, although the world is much simpler for agents. This allows for an examination of the precise micro-dynamics of learning and sharing with respect to team knowledge emergence.

The data can also be scaled up into meaningful micro – meso chunks. For example, human experimentation is generally structured as a series of different but related scenarios (i.e., trials within team) with exposure to a context difference (i.e., between team manipulation). Because the data encode the most elemental of acts, it can be examined to capture the micro-dynamics of learning and sharing within teams, within scenarios. This was the scaling when we

[10] Crisis Relief Operation: Naval Unit Simulation. Cronus is also the Greek God of time.
[11] CRONUS also tracks a deliberation and decision-making process, but they are not described to keep the discussion trackable.

used the knowledge emergence metrics to infer from the CM agent (droids) data where human teams (noids) would have difficulties. As shown in Figure 4, the graphs compare the proportion of knowledge acquired for exemplar agent (droid) teams on the left, relative to human (noid) teams on the right. The top panes compare droid and noid teams with variable learning rates / cognitive ability. Note the characteristic “plateau” that denotes a shift from a primary emphasis on learning processes to an emphasis on sharing processes. The plateau is due to the slowest team member holding up the rest of the team. The bottom panes compare droid and noid teams with commensurate learning rates / cognitive ability. Note the absence of the plateau. Instead, the teams progress seamlessly from a primary emphasis on learning processes to sharing processes. Thus, the process mechanisms undergirding the plateaus were used to trigger interventions to advise human teams how to ameliorate the bottlenecks represented by the plateau effect in Figure 4. However, one can also scale up to a focus on repeated scenarios, where the focus is on within team trajectory patterns and the between team differences in trajectories over time due to the manipulations (embedded agents, no agents). Such a focus can be analyzed using conventional applications of multilevel random coefficient modeling (Chao et al., 2013).

It is also worth noting that both the CM and CRONUS data are amenable to modeling through the use of most of the analytic techniques discussed in the prior section, including relational events analysis, dynamic network analyses, and machine learning / data mining techniques. For example, relational events analysis may be particularly insightful for the temporally precise CRONUS data because of its ability to model event sequences across different actors - receivers, handle complex temporal dependencies, and provide a basis to estimate parameters and assess uncertainty (Butts, 2008). In addition to conceptualizing team knowledge building as a series of events, one could view the process as a dynamic pattern of exchanges among team member actors. In this conception, actors are nodes and exchanges of information are links or edges. Dynamic network analysis is potentially useful in its ability to detect four types of network changes, including stability, evolution, shock, and mutation (McCulloh & Carley, 2009). An examination of stability would be akin to examining trajectories of the process over time and determining to what extent the changes vary between teams. Similarly, one would expect that teams would get better at managing exchanges over time, albeit differentially. The nature of this evolution could be examined. Shocks are external to the team and would represent manipulations that would require adaptation. If the shock prompted an adaptive change in the network, one would capture a mutation. Finally, as part of an inductive – deductive interplay, one could use machine learning / data mining techniques to search for patterns that are predictive of effective learning, sharing, and / or decision making. The decision task incorporates a priority structure: learning constrains sharing (cannot share what has not been learned), sharing constrains team knowledge (if it is not shared, the team does not possess it), and team knowledge constrains decision making (if it is not in the knowledge pool, it cannot influence the decision and the likely outcome is suboptimal). Thus, using inductive techniques to identify key variables and relations that maximize each phase of the process would be useful as a means to drive deductive research. Even a small, constrained, but targeted world can generate big data and offer many intriguing opportunities for theory building, evaluation, and application.

Concluding Thoughts:
Big Data and Advancing the Frontier on Process Dynamics

The promise of big data to advance scientific understanding and practical application – particularly in a mode of computational, data-driven, pure discovery – has to date primarily been realized in the physical sciences (e.g., biology, physics). The social sciences have been much slower to embrace the necessary techniques and approach (Lazar et al., 2009). Of course, there is also the issue of getting access to big data. Until recently, digital traces and other big data relevant to social interactions have been the province of nation states in cyber space (e.g., China, Russia, the NSA[12]), large international technology firms (e.g., Google, IBM, Yahoo), and the retailer – credit card complex. Indeed, Lazar et al. (2009) warn that: "Computational social science could easily become the almost exclusive domain of private companies and government agencies. Alternatively, there might emerge a "Dead Seas Scrolls" model, with a privileged set of academic researchers sitting on private data from which they produce papers that cannot be critiqued or replicated. Neither scenario will serve the long-term public interest in the accumulation, verification, and dissemination of knowledge" (p. 2).

However, this is changing and it is changing rapidly. Lazar et al. (2009) also describe an array of technologies that promise to bring big data to social science research including extensive video recording, digital traces (e.g., email, chat, GPS, and Internet data), and sociometric sensors. The use of deployable, wearable sensors is exploding in the form of applications on smart phones and physical activity monitors. Technologies that seemed far-fetched not so long ago (Goodwin, Velicer, & Intille, 2008) are now an integral part of everyday modern life. There are rapidly emerging and maturing technologies that enable the relatively unobtrusive collection of big data on social interaction phenomena. The future is here!

The advent of multilevel theory and research methods (Kozlowski & Klein, 2000) has had a substantial influence on OPB research, particularly with energizing the widespread interest on linking micro, meso, and macro phenomena. Teams – at the meso level – are at the juncture of major systems forces: the macro context and micro-level of emergent phenomena. There has been an explosion of multilevel research over the last fifteen years, but a large majority of that research has continued to rely on conventional research design and measurement tools. It is largely based on cross-sectional, static designs with measurement mostly using retrospective, self-reports of internal traits and states. This has not changed fundamentally for a century. But change is upon us now. The new technologies, tools, and

[12] http://www.nytimes.com/2011/11/04/world/us-report-accuses-china-and-russia-of-internet-spying.html?_r=0 (accessed 4 September 2014).

techniques of a computational social science make it possible to directly study team process dynamics and emergent phenomena (Kozlowski & Chao, 2012). Process dynamics are the next frontier for the science of team effectiveness … and for multilevel OPB research more broadly.

Our focus in this chapter has been to describe how big data can be harnessed to unpack team dynamics. The data are not “big” in the sense of world wide web digital traces (which are very big but also very messy). Rather the big data are intentionally targeted around a focal phenomenon. A typical medical team study we conduct yields approximately 10 thousand data points (codes) across 60 teams for a 20 to 30 minute team process and performance scenario and 20 thousand data points when 2 scenarios are used. The magnitude of the data scales up from there very rapidly. The CM data are another order of magnitude higher. Our initial validation runs for a simple CM generated approximately 22.375 million targeted data points. The coupled human task simulation tracks 133 data points across approximately 3800 time samples for each person in a typical experimental investigation. That generates approximately 500 million data points (e.g., about 240 teams of 3 people). The monitoring badges with their multi-modal data sampling at high frequencies, yield approximately 250 million data points for one HI-SEAS team of 6 members over a four month scenario, 500 million for 8 months, and 750 million over 12 months. Compared to conventional team effectiveness studies conducted in the lab or field, these data sets are several orders of magnitude larger, but precisely targeted. This targeted big data approach holds great promise for unpacking the team process emergence and team dynamics.

The advent of new technologies and the big data they generate will fuel research on this new frontier. They promise to free researchers from the limitations of self-reported survey data as the primary measurement technology. Self-reports will still have utility, of course, but they will not be the primary or only observational method. The new measurement tools promise to be less obtrusive. Video and wearable sensors do not intrude and interfere with an ongoing stream of behavior. ESM is somewhat intrusive, but it is quick. Some tools hold the promise to collect behavior and interaction data at near continuous frequencies. Higher sampling rates mean that micro-process dynamics can be captured and scaled up to any higher-level meaningful aggregate. And, the tools hold the promise of being more objective. You can be asked "to what extent" you feel aroused on a 1 (low) to 7 (high) Likert scale, and you may be able to provide a reasonably reliable and valid self-report. But, with a heart rate monitor assessing your heart rate and its variability across contexts and interactions, arousal can be established relative to baseline. It's not just a perception.

These tools, and the big data they generate, have much promise for enabling investigators to unpack process dynamics and emergent phenomena. However, challenges remain with respect to targeting research design on meaningful phenomena; balancing deductive and inductive approaches; and aligning research design, measurement, and analysis to enable solid inference. We do not envision a computational social science as a process of collecting big data willy-nilly, throwing it into a blind data-mining analysis, and "discovering" new phenomena or relationships. Rather, big data techniques need to be targeted and appropriately harnessed to generate meaningful insights. The purpose of our chapter was to highlight these key research design considerations and to illustrate, using different research examples, ways in which these technologies, tools, and big data techniques can be used to study team process dynamics. We highlight the illustrations in Table 1. We hope the insights we shared are useful to other investigators.

Finally, a closing thought. As investigators begin to use these tools and techniques more widely, theory will need to be more explicit about the nature of process dynamics (i.e., what types of dynamics), how processes evolve, and how they vary for particular substantive phenomena of interest. This advance in theoretical precision can only occur with the assistance of inductive methods that improve our descriptive understanding of process dynamics and the mechanisms that drive dynamic phenomena. Theory in OPB is light on process dynamics and one cannot construct more precise theory without good descriptive data. Moreover, without good theory, one may not be able to make sense of dense, “big,” observational data sets (e.g., 270 days of ESM data coupled with 270 16 hour days of badge data). The multiple, continuous data streams and the end-of-day measures need to be fused and nonlinearities identified. This will likely necessitate the use of inductive data mining techniques to develop an understanding of the dynamic patterns characterizing phenomena. This sort of induction then needs to be coupled with deductive methods to verify that the inferred patterns are robust and replicate across multiple settings and samples. Big data call for an active interplay between theory building and theory testing; an interplay between induction and deduction.

Notice that in our description above we deliberately used the term “phenomena,” rather than constructs. A focus on process dynamics and emergence will force theory to become more principled and system oriented (Kozlowski et al., 2013). Narrow “boxes” (i.e., constructs) and “arrows” (i.e., hypothetical linking mechanisms) models are tractable for making sense of static or very limited “chain-like unidirectional cause – effect relationships” (McGrath et al., 2000, p. 97), but they are not tractable for modeling dynamic phenomena (except over very short time slices). Investigators on the frontier are innovating how they conceptualize, measure, and make sense of dynamic behavioral phenomena. OPB as a field will need to innovate notions of theory, phenomena, and constructs too.

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Figure 1. Medical Team Simulation Suite

Figure 2a. Medical Team Dynamic Process Model

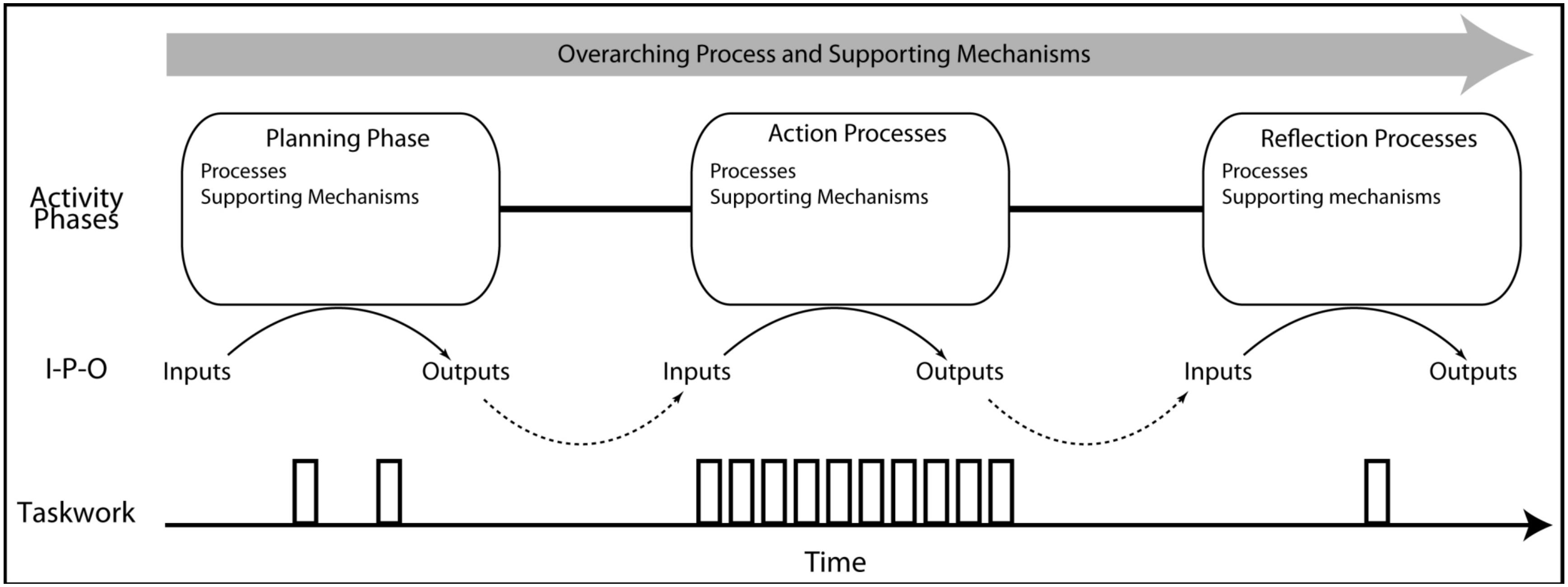

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Figure 2b. Event Time Windows and Scenario Timeflow.

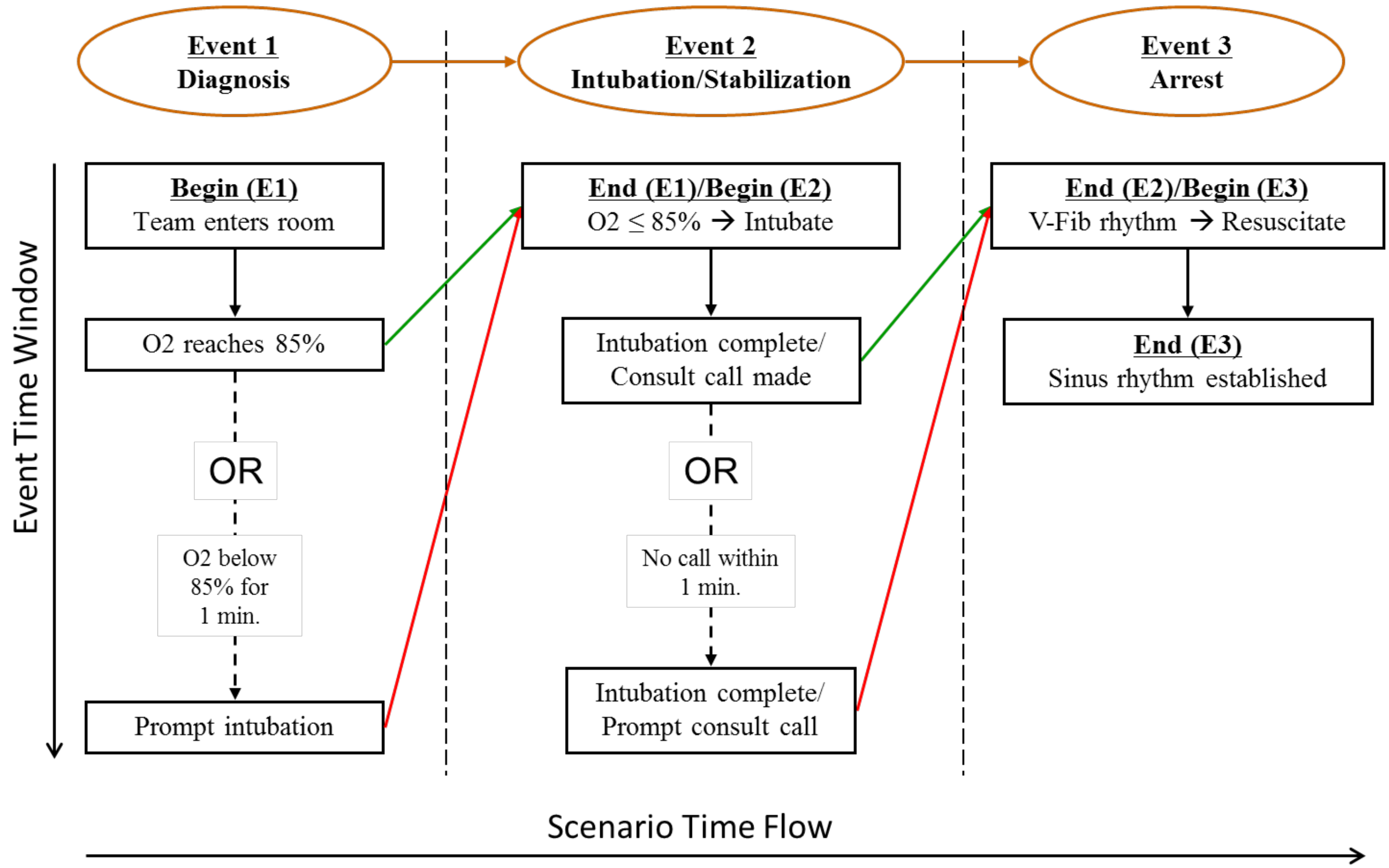

Figure 3. NASA Spaceflight Research Analog Environments.

HERA (Photo by C.-H. Chang).

HI-SEAS Mission 2: Day and night (Photos by Ross Lockwood).

NEEMO Mission 16 (Photo courtesy of NASA).

Antarctic science teams camped on the ice.

Figure 4. Comparison of agent (droid) and human ('noid) team knowledge acquisition.

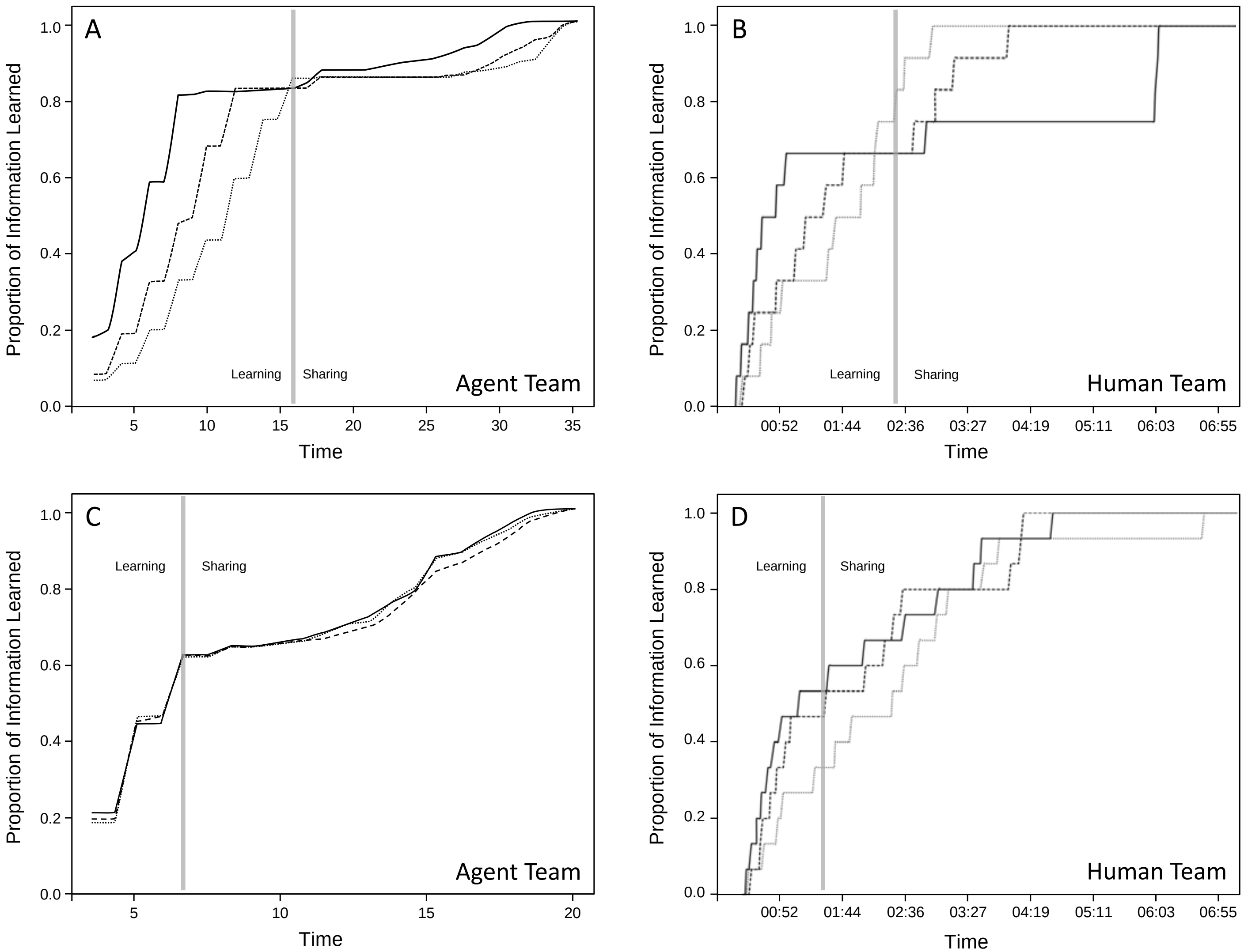

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Table 1. *Examples of Big Data in Research on Team Process Dynamics*.

Research Design and Example	Big Data	Deduction -- Induction	Alignment and Analytics
High fidelity simulation Example: Emergency medical teams	Coding HD audio/videos on SME validated behaviors related to teamwork and taskwork (medical care)	Deduction: apply OPB team process measurement to medical team context Induction: examine individual behaviors to identify appropriate leadership dimensions	Alignment: HD video provides rich stream of data that can be coded in multiple ways to capture temporal and team processes Analytics: Structural equation modeling; Regression-based pattern recognition analysis
Experience Sampling Methods Example: Teams in isolated, confined, and extreme environments (NASA)	Physical, physiological, and behavioral data from wearable sensor system	Deduction: workload manipulations may stress quality of team member interactions Induction: data streams may identify new team profiles or non-linear patterns of team interactions	Alignment: Intensive longitudinal data may identify team interaction patterns across different contexts and durations. Analytics: Autoregressive integrated moving average models; Latent vector autoregressive models; Relational events analysis
Simulation and Computational Modeling Example: Teams learning and sharing information for decision making	Agent-based simulations (droids) allow virtual experiments on thousands of teams. Human teams (noids) operating in a computerized synthetic team task allow data capture at the click level.	Deduction: Agents are designed to minimize errors and bottlenecks for human teams, based on patterns observed in CM / ABS Induction: Patterns of knowledge emergence were observed under different conditions of teammate characteristics	Alignment: Team knowledge emergence results from CM / ABS can help design human experimentation. Knowledge emergence is tracked across scenarios within and between teams. Analytics: CM / ABS