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Time to go wild: How to conceptualize and measure process dynamics in real teams with high resolution

Abstract

Team processes are interdependent activities amongst team members that transform inputs into outputs, vary over time and are critical for team effectiveness. Understanding the temporal dynamics of team processes and related team phenomena with a high resolution lens (i.e., methods with high sampling rates) is particularly challenging when going "into the wild" (i.e., studying teams operating in their full situated context). We review quantitative field studies using high resolution methods (e.g., video, chat/text data, archival, wearables) and map out the various temporal lenses for studying team dynamics. We synthesize these different lenses and present an integrated temporal framework that is of help in theorizing about team dynamics. We also provide readers with a "how to" guide that summarizes four essential steps along with analytical methods (e.g., sequential and pattern analyses, mixed methods research, abductive reasoning) that are applicable to the broad scope of high resolution methods.

Keywords: team dynamics, statistics/methods, time, field research, video, chat, wearables, sport teams

Understanding team processes – i.e., “members’ interdependent acts that convert inputs to outcomes through cognitive, verbal, and behavioral activities” (Marks, Mathieu, & Zaccaro, 2001, p. 357) – is fundamentally important to help improve team performance outcomes in organizations (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). For example, during a medical surgery, teams dynamically engage in multiple interdependent activities such as coordination (e.g., sequencing actions to operate the patient, preparing patients for activities carried out by others), monitoring (e.g., communicating symptoms to other team members), and focusing on goal accomplishment (e.g., operating on the patient, repairing injuries). How effectively surgical teams engage in such processes has important implications for outcomes such as adverse events and patient health (e.g., Schmutz, Hoffmann, Heimberg & Manser, 2015).

Crucial to understanding effective team processes is recognizing that they are dynamic phenomena that change over time (e.g., Kozlowski, 1999; Kozlowski, 2015; Leenders, Contractor, & DeChurch, 2016; Luciano, Mathieu, Park, & Tannenbaum, 2018; Rousseau, Aubé, & Savoie, 2006; Schecter, Pilny, Leun, Poole, & Conractor, 2017). First, the nature and extent of team processes can change in response to internal contingencies (e.g., voicing frustrations might stimulate team conflict management) and external contingencies (e.g., during surgery, rapid changes in a patient’s body temperature will trigger backup behaviors). Second, team processes may differ in their consequences across team episodes (Marks et al., 2001). For example, planning and preparation activities may be more important for team effectiveness during early episodes and less important during action episodes (Maynard et al., 2012). To adequately map these team dynamics, higher sampling frequencies than typically used in organizational behavior research are needed (Kozlowski, 2015; Mathieu & Luciano, 2019; Schecter et al., 2017).

One approach to capturing these dynamics is to repeatedly survey team members, which can be especially useful (and even necessary) to capture team phenomena that are inherently latent (e.g., phenomena like silence, cf., Meinecke, Klonek, & Kauffeld, 2016) or have low levels of observability (e.g., team cohesion, cf., Carter et al., 2015). However, survey-based methods have their limitations for doing intensive repeated measurements in the field (Driskell, Driskell, & Salas, 2017; Khawaja, Chen, & Marcus, 2012; Kozlowski, 2015). To illustrate, imagine a researcher who seeks to understand the temporal contingencies of team coordination and its effect on patient outcomes in medical teams (e.g., Farh & Chen, 2018; Schmutz, Lei, Eppich, & Manser, 2018). To survey behaviors during surgical procedures, the researcher would need to interrupt the team members repeatedly during the surgery, whilst they are in the middle of cutting open the patient, with their attentional resources being focused on patient needs. Such an approach can interfere with naturally occurring team processes and possibly induces 'testing effects' that change the nature of the phenomenon itself (Cook & Campbell, 1986) as well as lead to participant withdrawal. Furthermore, it may distract team members from focal tasks (and thus can put people at risks, particularly in medical contexts, Bell, Fisher, Brown, & Mann, 2016), which is highly questionable from an ethical perspective (Driskell et al., 2017; Farh & Chen, 2018).

Accordingly, studying real teams often benefits from methods that do not interrupt ongoing interactions and that provide a high (i.e., "movie-like") temporal process resolution of team dynamics (Kozlowski, 2015; Leenders et al., 2016). In this paper, we focus on such high resolution approaches, which we define as methods with *high sampling rates* that allow to capture team dynamics 'in the wild'. Teams in the wild are teams acting "in their full situated context" (Salas, Cooke, & Rosen, 2008, p. 544). Studying teams within their actual task context is relevant from a socio-technical systems perspective (i.e., optimizing work by understanding the interactive effects of both social and technical aspects of the system, Cummings, 1978) because the nature of the tasks and systems in which a team operates affects team processes and performance outcomes (Salas et al., 2008). This perspective implies that many team phenomena originate and develop “in situ”, that is, within real contexts. Whereas experimental paradigms and laboratory research are legitimate ways to study team phenomena in isolation, assess internal validity, and allow inferences on causality (Allen & O’Neill, 2015), the science of teams also needs approaches with high external validity that focus on teams within their natural habitat. This entails teams that work on real tasks and are embedded in specific organizational environments that shape, maintain, and constrain unfolding team interaction processes (Johns, 2006).

Accordingly, our goal in this article is to unpack how high resolution measurement techniques have expanded – and can continue to expand – the field’s understanding of temporal dynamics that occur within real-life teams. To reach this aim, we review team studies that have adopted high resolution measurement techniques and that thereby have contributed to different literature streams (organizational behavior, communication, and team sports). Furthermore, time-dependent effects remain undertheorized and understudied (Kozlowski et al., 2013; LePine et al., 2008; Roe, Gockel, & Meyer, 2012), a shortcoming that is particularly pertinent in real teams that are “complex and confusing […] entities” (Waller & Kaplan, 2018, p. 501) and characterized by multifarious processes. Current models fail to specify exact time scales and durations of how team processes change, which makes it hard to identify sampling rates and measurement points for research designs (Leenders et al., 2016; Mitchell & James, 2001). Accordingly, we also seek to expand theory about when, why, and how teams change over time (Mitchell & James, 2001).

In what follows, we first provide a review of the extant literature. Based on the review, we introduce the notion of aligning a phenomenon’s time span with different measurement approaches, and we introduce concepts of help to do this. We also describe key attributes of the studies included in our review, such as the industry and team contexts in which high resolution methods have been typically used, and we describe key approaches to using high resolution methods. After the review, we synthesize the observations from the review into an integrated framework of team process dynamics that we propose to help move the field forward. Finally, we provide "how to" guidelines for high resolution approaches to encourage researchers in adopting these non-traditional methods.

A Review of the High Resolution Team Literature

How have high resolution methods contributed to a temporally refined understanding of team dynamics? To answer this question and identify relevant gaps in the literature, we conducted a literature search to find studies focusing on team dynamics using high resolution methods in the wild (Appendix A provides details on our search strategy). Consistent with the idea of "the open, systemic, and dynamic nature of real-life teams" our review includes teams "with more or less clear or stable boundaries and co-dependencies" (Humphrey & Aime, 2014, p. 449). In other words, we follow the notion to "relax the definitional elements of what makes a real team and explore what is interesting in contemporary collaboration" (Wageman, Gardner, & Mortensen, 2012, p. 312). Such a broader conceptualization of teams allows researchers to keep track with the changing ecology of the modern working world and thereby continue to study interesting and new phenomena (Roe et al., 2012).

We consider high resolution methods as comprising a variety of approaches that allow the measurement of a phenomenon with *high to near-continuous sampling rates* (Kozlowski, 2015). Crucially these methods need to take into account the time span over which a whole phenomenon unfolds, that is, the temporal scope of the phenomenon. For example, a phenomenon like emotional mimicry unfolds within seconds, thus studying its dynamics would require sampling the phenomenon with a fine-grained millisecond resolution.

In contrast, a phenomenon like team burnout could develop over several months or even years, thus, studying its dynamics would require sampling it with weekly to monthly rates. Moreover, when studying teams in the wild, high resolution methods may require to be *unobtrusive* as it is difficult and sometimes even ethically questionable to interrupt teams while they are working on task accomplishment. That is, high resolution methods that offer non-reactive measurements can be advantageous when trying to study a dynamic team phenomenon “in vivo” (Hill, White, & Wallace, 2014).

Using the outlined definitions, we identified 42 studies in the review of the extent literature that met our search criteria (see Appendix B). The identified team studies cover many industries (Table 1, column *industry*) and contexts (Table 1, column *context*). Yet, we noticed that high resolution research is particularly prominent in the context of *action teams* which have highly trained members operating under variable workload and uncertainty (Ishak & Ballard, 2012). Action teams can be found in a variety of industries: e.g., aviation (i.e., flight crews; e.g., Lei, Waller, Hagen, & Kaplan, 2016, Waller, 1999), healthcare (i.e., medical teams; Farh & Chen, 2018; Kolbe et al., 2014; Schmutz et al., 2015; 2018; Zijlstra, Waller, & Phillips, 2012), crisis management (e.g., Stachowski, Kaplan, & Waller, 2009; Waller, Gupta, & Giambatista, 2004), and in professional sports (e.g., Grijalva, Maynes, Badura, & Whiting, 2019; Halevey, Chou, Galinsky, & Murningham, 2012; Stuart & Moore, 2017).

Next, we unpack two key insights from our analysis of the theories and methods used in these studies. The first insight pertains to issues of how research treats time and resolution. The second insight concerns different approaches to analyzing team dynamics. The following section helps organize the complex literature of team process dynamics and time scales by developing these two key theoretical directions. With respect to the issue of temporal resolution, we highlight the value of using episodic and development team models and point out how these models focus on phenomena of different temporal scale. With respect to the issue of analytic approaches, we organize the existing literature into three approaches that have been applied to analyze high resolution data and discuss how they inform knowledge about team dynamics.

-----Insert Table 1 here-----

Time and resolution. A key important observation from the review is that studies vary widely with respect to how they operationalize temporal resolution, defined as the number of repeated measurements captured within the phenomenon's time span. For example, some studies have sampled team process data multiple times per minute throughout a one-hour performance episode (e.g., Schecter et al., 2017). This reflects a high resolution approach (albeit using a short time span, as we discuss later). Other studies have collected data multiple times per week over two years (e.g., Stuart & Moore, 2017), which is also a high resolution approach (albeit using a longer time span). Both examples would be considered high resolution, although the focal phenomenon respectively occurred and unfolded within different time spans (i.e., short versus long), necessitating measurement with different granularity.

Hence, it is important to acknowledge that dynamic phenomena can theoretically unfold over different time spans. An initial concept of help is to distinguish between two families[1] of temporal theories: *Episodic theories* and *developmental theories* (see Table 2, column 1). Episodic theories focus on specific team performance episodes of concrete task work during which the team works towards common goals (i.e., "periods of time over which performance accrues and feedback is available", Marks et al., 2001, p. 359). In the high

[1] We use the broader term ‚families' here because there are multiple variants of both episodic and developmental theories

resolution literature, an example for a team performance episode could be an operation carried out by a medical team (Kolbe et al., 2014) or a flight conducted by a crew of pilots (Lei et al., 2016). Developmental theories have a long-term perspective and specify how teams mature over time and/or go through different qualitative stages, specifying how team phenomena change over larger time spans (e.g., Tuckman & Jensen, 1977). An example of developmental theory in the high resolution literature is research on team performance recovery in ice-hockey teams unfolding over multiple games resulting of adaptive dynamics in team configurations over two years (Stuart & Moore, 2017). Both temporal theories are closely connected, such that episodes are usually nested within the long-term developmental life-cycle of a team. For example, from an episodic lens, a healthcare team may engage in dynamic interactions during a single surgery, which constitutes an area of research focusing on micro-dynamic interactions between team members. In contrast, from a developmental theory lens, the same team may also go through dynamic changes over multiple weeks (and surgeries), thus offering an opportunity to study long-term team dynamics.

-----Insert Table 2 here-----

Episodic theory operates on a smaller time span than developmental theory. In other words, developmental theory should focus on team phenomena that unfold over larger time spans, that is, the dynamics and temporal changes of these phenomena unfold over days, weeks, months, or even years. Of note, the focal team phenomenon of interest should always dictate when repeated measurements are taken. That is, considering and carefully conceptualizing the *time span of the whole phenomenon* is crucial in identifying appropriate high resolution methods. To give an example (Table 2, column *example phenomenon*), emotional mimicry and emotional contagion are both socially dynamic phenomena. The literature suggests that emotional mimicry emerges and changes within seconds (Dimberg & Thunberg, 1998). For emotional contagion, the time span is supposed to be a little bit larger and entail multiple seconds to multiple minutes (e.g., Barsade, 2002; Lehmann-Willenbrock et al., 2011). Hence, to align theory and methods, our recommendation would be to theorize about the dynamics of these phenomena using an episodic lens. In contrast, team negative affect is also a dynamic phenomenon but has a larger time span — most likely displaying weekly or monthly dynamics (Knight, 2012; Paulsen, Klonek, Schneider, & Kauffeld, 2016). Finally, some dynamic team phenomena, such as collective burn-out (Gonzalés-Morales, Peiró, Rodríguez, & Bliese, 2012), have an even larger time span, that is, they could unfold and change over months or supposedly years.

Taken together, the concept of "high resolution" is essentially a relative term that requires specification of the parts (i.e., the repeated measurements) and the whole (i.e., a phenomenon's time span). That is, the studies that we reviewed have all collected repeated observations (i.e., "parts"), but our review showed that research varies significantly how the researchers operationalized the focal phenomenon time span (i.e., "whole"[2], see Table 2). For example, some studies studied a whole phenomenon with high resolution across a 1-hour period, while others studied the dynamics of a phenomenon over months. To provide a scientific analogy for the parts-versus-whole problem, think about two phenomena of different scope, for example, "oceanic currents" and "submarine bacteria". Both phenomena can be studied with high resolution methods (e.g., satellites and microscopes), but a high resolution image of oceanic currents would be a low resolution map of bacterial activities that live in these oceans. Both oceanic dynamic current flows (macro) and bacterial processes (micro) offer ways to understand global climate dynamics. However, empirical findings

[2] We computed the *temporal resolution* for each study by dividing the number of repeated observations (i.e., the parts) by the overall observation period (i.e., the researchers' operationalization of the "whole" phenomenon time span).

obtained with one high resolution method (i.e., satellites capturing dynamic oceanic currents) operate on a different theory level than findings obtained with another method (i.e., microscope about micro-biological dynamics in the oceans). While both types of research may focus on related problems (i.e., geo-temporal dynamics that affect our global climate) and both use high resolution methods, they use methods with fundamentally different scopes for capturing the respective phenomena. Arguably, the use of different scopes also has profound implications for the study of team dynamics.

To illustrate this notion of relativity, we can take into account the time span of a dynamic phenomenon and ask: When should the parts of the phenomenon be measured (see Table 2, column four)? That is, dynamic phenomena that have a large time span require different sampling intervals than dynamic phenomena that have a short time span. Technically, the level of measurement reflects the actual data source, that is, "the unit to which data are directly attached" (Klein et al., 1994, p. 198). This illustrates the parts-versus-whole issue of which researchers need to be aware. In other words, researchers need to think at what time intervals they should collect "parts" of the "whole" phenomena to properly model the dynamics of the phenomenon (i.e., how is the whole phenomenon unfolding and changing over time?). To illustrate, a phenomenon like emotional mimicry has been argued to have a short lifetime and can emerge and disappear within a second (Dimberg & Thunberg, 1998). Hence, understanding temporal dynamics of emotional mimicry would require researchers to collect multiple "parts" of the "whole" phenomena with almost a millisecond precision.

Furthermore, we provide suggestions that point out which high resolution methods best align with phenomena of different time span (Table 2, *column five*). For example, physiological measures captured via ambulatory wearables and tracking devices constitute high resolution data that offer precision on the second (e.g., Wundersitz et al., 2015;

Bernstein & Turban, 2018; Saavedra et al., 2011) and would thus be suitable to study phenomena such as emotional mimicry. On a broader time span, high resolution data from coded video-recorded team activities (Waller & Kaplan, 2016) have shown to provide multiple measures per minute (for example studies, see Table 1) and hence allow to study micro-dynamic team phenomena that unfold within relatively short team episodes. To illustrate, Lei et al. (2016) measured changes in team communication multiple times per minute to model how different interaction patterns related to team adaptive crew performance during flights. However, researchers could even consider archival records (which provide repeated measurements of team data over weeks, months, or years) as a high resolution method. For example, Grijalva et al. (2019) used archival data to capture team coordination multiple times over the course of a basketball season and used the temporal order of games to model changes in the relationship between team composition features and team coordination.

Applying our proposed categorization to the existing literature, Table 1 shows illustrative studies organized according to these concepts. In the column *temporal theory,* we classified research into the two categories of *episodic* (e.g., medical procedures, flight simulations) and *developmental theories*. It is noteworthy that some phenomena (e.g., team coordination) have been studied from both an episodic and a developmental theoretical perspective. For example, Kolbe et al. (2014) used an episodic-lens and measured team coordination repeatedly over minutes (Table 1, column *indicator of temporal resolution*). In contrast, Grijalva et al. (2019) employed a developmental lens and measured team coordination repeatedly over weeks.

Multiple approaches. In our review of studies (see examples in Table 1), we also identified three approaches for analyzing team dynamics. First, some researchers use what we refer to as the *static approach* because it focuses on between-team differences (assuming that team processes are static) to explain differences in team outcomes. Studies within this category present theoretical arguments to focus on fine-grained processes and then – despite using high resolution methods for data collection – summarize fine-grained process data (over time) to form an aggregate variable. While such a summary reduces the complexity of the data and simplifies the analysis of linkages between team processes and team outcomes, it comes at the expense of truly capturing temporal dynamics. For example, Kauffeld and Lehmann-Willenbrock (2012) argued for the importance of uncovering micro-level interaction processes and used video-recordings as a high resolution method to measure dynamic team communication. However, the authors then aggregated the number of specific communication events over time for each team and used this time-aggregated measure to predict team effectiveness. Using time-aggregates of "process" measures to predict some team outcome variable has one problem: This approach discards any form of temporal process variability and, hence, does not contribute towards a better understanding of temporal dynamics. An implicit (or explicit) assumption of this approach is that team activities are more or less stable over time and hence "process" is treated as a static variable (Kauffeld & Lehmann-Willenbrock, 2012; Schmutz et al., 2015). Typically, researchers adopting this approach seek to understand if and how team processes (i.e., team coordination, planning behavior etc., see Table 3) explain variance in team effectiveness (e.g., Kauffeld & Lehmann-Willenbrock, 2012; Schmutz et al., 2015). Accordingly, hypotheses are formulated in a way that makes static comparisons between teams: "Effective teams will show more/less of behavior X than ineffective teams".

The static approach still has research design advantages. That is, high resolution methods using a static approach may mitigate common-method problems if, for example, the team processes are measured with a non-traditional method and other phenomena are measured with a different method (e.g., self-report surveys). However, whether researchers use a time-aggregate of a team process variable to predict team performance or if they survey team members about the process (e.g., team coordination) and relate this self-report measure to team performance are just two different methodological approaches to answer the same question (the first one using a multi-method, the latter using a mono-method approach). In other words, research from the static approach does not necessarily yield more time-theoretical insights than research using traditional methods. What is missing from this approach are questions that directed towards understanding at what time team activities were most beneficial for team performance. How did activities within the team change over time? How patterned are these team interactions?

A second approach used by researchers, which we refer to as *multiphase and socio-technical*, goes towards addressing questions about team dynamics. This approach is grounded mostly in episodic theories (e.g., the temporal multiphase theory from Marks et al., 2001) and socio-technical theory by taking into account that team processes differently affect team outcomes depending on the changing nature of the task itself (e.g., Leenders et al., 2016; Mathieu et al., 2008; Roe et al., 2012). An example high resolution study from the multiphase and socio-technical approach is how effective flight crews adapt their behaviors according to the changing nature of routine versus non-routine tasks over the course of a performance episode (Lei et al., 2015).

A third approach, which also helps to understand team dynamics, is what we refer to as *process dynamics*. In this approach, researchers try to understand how two (or more) team phenomena show systematic patterns over time (McGrath & Tschan, 2004; Pilny, Schecter, Poole, & Contractor, 2016). The core assumption is that team processes display systematic temporal patterns. Hence, this perspective fundamentally focuses on co-variations and contingencies of distinct team activities over time. A research hypothesis from this perspective needs to point out temporal variations (e.g., “Over time, team behavior X elicits/ is associated with team behavior Y"). An example study following the process dynamics approach is the work by Kolbe et al. (2014) showing how effective healthcare teams sequence their activities differently over time when compared to ineffective teams.

Summary of the state of the literature. In summary, the literature examining teams with high resolution has refined our understanding of team dynamics. While much has been learned from this research, we noted considerable variation in temporal resolution that studies have used, and in the overarching analytical approaches that were applied to generate novel knowledge about team dynamics. Furthermore, studies have not well articulated the time spans for focal team phenomena and we discussed problems that arise when high resolution approaches and focal phenomena are misaligned. In what follows, we argue there is a need to synthesize these novel concepts and approaches into a coherent and comprehensive framework.

Proposed Framework For Understanding Team Dynamics with High Resolution

In this section, we integrate our observations from the literature and provide a framework that should help researchers to conceptualize and study team dynamics with different high resolution methods (Figure 1). The framework can be applied to different time spans and is applicable to the various contexts in which field researchers may study real teams. Our framework especially focuses on the multiphase/socio-technical and the process dynamics approach as they truly capture temporal dynamics (unlike the static approach).

-----Insert Figure 1 here-----

The heart of our framework is the center of Figure 1. As can be seen in Figure 1, team dynamics occur both within performance *episodes* and within the life-cycle of *team development* (see Figure 1, as discussed in Table 2). Team episodes comprise situations of intensive interdependent work on a specific task to achieve common goals, while team development reflects the maturation of the team over larger temporal frames. These temporal theories (episodes versus team development) can be mapped onto different phenomenon time spans. The center of Figure 1 shows that team phenomena can display both fluctuations within a single performance episode but also across team development (i.e., phenomena that operate on broader time span need to be captured across multiple episodes). Hence, this framework takes into account that dynamics of some phenomena can unfold on radically different time spans (e.g., seconds, weeks, months, or even years) and thus require different high resolution methods. To depict this, we added icons that remind the reader about our earlier analogy of using microscopes versus satellites to study phenomena of radically different scope.

First, the process dynamics approach assumes that processes exhibit systematic patterns and these dynamic interaction patterns shape team emergent states (i.e., manifestations of collective phenomena at the team-level, Cronin et al., 2011). These systematic patterns between a phenomena and time could look very different depending on a phenomenon's time span (e.g., is the whole phenomenon unfolding over minutes, weeks, or months?). This reminds the reader to use high resolution methods that are well aligned with the phenomenon's time span.

Second, process dynamics can also be affected by specific phases (e.g., early phase versus late phase), and by dynamic aspects of the team task itself (e.g., temporal variations in workload). This integrates the socio-technical perspective by proposing that teams must execute different processes at different times, depending on task demands. For example, when teams are working on a simple task, they may be more effective when they also engage in simple temporal interaction patterns (i.e., following a standardized sequential procedure). However, as tasks increase in complexity, teams may also engage in more complex process dynamics (which may require more complex temporal interaction patterns).

In the next section, we unpack the two major time-theoretical approaches that are at the heart of our framework in Figure 1. In Table 3, we also outline prototypical research questions and contrast them against typical research questions stemming from the static approach.

-----Insert Table 3 here-----

The Multiphase and Socio-Technical Approach

As discussed earlier, the *multiphase and socio-technical approach* is mostly grounded in episodic theories (e.g., Marks et al., 2001) and builds on the core assumption that teams should execute different behaviors at different times during a specific episode in order to be effective. The socio-technical approach incorporates the notion that team processes affect team outcomes depending on the changing nature of the task itself (e.g., Leenders et al., 2016; Marlow et al., 2018; Mathieu et al., 2008). Research questions from this approach ask if and how team processes (e.g., conflict, workload sharing, communication, or coordination) increase or change over distinct team tasks of a performance episode (e.g., a surgery, a flight, or a mission; e.g. how does team reflexivity change over the course of a performance episode?).

This approach advances theory by comparing fluctuations of team processes across different team phases (e.g., Schmutz et al., 2018; Manser et al., 2008) or across varying task levels (Hoogeboom & Wilderom, 2019; Lei et al., 2016), thus, challenging assumptions from the static approach by recognizing that activities are contingent on dynamic task characteristics. Teams are part of socio-technical organizational systems and changes of the technical system are tightly related with changes of the social system, that is, the extent to which specific activities play a fundamental role for team performance (Rousseau et al., 2006; Tiferes & Bisantz, 2018; Waller, 1999). This process approach has studied how volatile task features affected team process dynamics in medical emergency teams (Manser et al., 2008) and flight crews (Waller et al., 2004). For example, flight crews change their communication patterns when they encounter unexpected events (David & Schraagen, 2018), cardiac anesthesia teams adapt their coordination processes contingent on the level of task interdependence during an operation (Manser et al., 2008), and health care teams increase reflection processes over time during medical emergencies (Schmutz et al., 2018).

The Process Dynamics Approach

The *process dynamics approach* is trying to understand systematic patterns of multiple team phenomena over time (McGrath & Tschan, 2004; Pilny et al., 2016). The core assumption is that team processes display systematic temporal patterns. Hence, this perspective fundamentally focuses on co-variations and contingencies of distinct activities over time. A research hypothesis from this perspective needs to point out within-team variations that occur over time (e.g., "Within team interaction processes, behavior X elicits behavior Y"). Illustrative research includes questions like "How do temporal variations in team coordination affect temporal variations in team performance?" or "Do teams show systematic sequential behavior patterns during a surgical operation?". The process dynamics approach can yield both insights about dynamics regarding phenomena with short time spans (e.g., *communication sequences,* Bowers, Jentsch, Salas, & Braun, 1998, *emotional contagion*, Lehmann-Willenbrock, Chiu, Lei, & Kauffeld, 2017) but also about dynamics regarding phenomena with larger time spans (e.g., how do different personalities within a team affect team coordination when team familiarity is increasing over multiple performance episodes, cf., Grijalva et al., 2019).

Future research using this approach can advance our knowledge even further by taking into account both the socio-technical and process dynamics approach. For example, a researcher could use paradox theory to argue how teams require both highly flexible but also highly structured team temporal interaction patterns to be effective (Schad, Lewis, Raisch, &

Smith, 2016). On the one hand, adherence to protocols should allow teams to operate most efficiently (Kanki, Folk, & Irwin, 1991), but on the other hand, teams that work together in a predictable manner are less agile and cannot respond to changing task demands (Hollenbeck, Ilgen, Tutle, & Sego, 1995). The paradox of these competing demands ("be flexible" versus "be structured") can be resolved by integrating the social-technical approach. More specifically, the researcher can develop hypotheses that denote how teams need different levels of process dynamics (flexible versus structured interaction patterns) when working on different task types during (or across) performance episodes. That is, routine tasks may require teams to be aligned and structured in their communication, whereas non-routine tasks may require flexible interaction patterns (Waller, 1999). While this integrated perspective is rather new, initial attempts have found promising results that showed how effective teams switch between temporal patterns when they work on routine tasks and flexible interaction patterns when they work on non-routine tasks (Hoogeboom & Wilderom, 2019; Lei et al., 2016; Stachowski et al., 2009).

Antecedents of Team Dynamics

Finally, our model also incorporates input factors on multiple levels that will have an impact on these team dynamics (see left-hand side of Figure 1). That is, we acknowledge that team processes are affected by individual team member characteristics (e.g., personality, knowledge and abilities), team-level input variables (e.g., team size, gender composition, etc.), and organizational contexts (e.g., team-based HR policies, organizational climate). System variables characterize the team as a whole and do not vary for a given performance episode but they may change over the course of team development.

Creating Novel Insights with High Resolution Methods: A "How To" Guide

So far, we have reviewed the literature and presented an integrated framework to orient high resolution research. Our temporal framework has pointed out that team phenomena can unfold, emerge and be studied over radically different time spans. Since we have introduced methodological concepts (as opposed to substantive theoretical concepts), we further believe it is also necessary to make arguments about how to use these methodological concepts which will help improve the rate of absorption about theories that deal with team dynamics (van Maanen, Sørensen, & Mitchell, 2007). Therefore, in the next section, we provide methodological guidance for researchers who want to adopt high resolution methods. Specifically, Table 4 summarizes four major steps when studying teams with a high resolution approach: (1) identification of research questions, (2) data collection and management, (2) data analysis, and (4) interpretation of results. As such, readers can view Table 4 like a movie trailer that outlines relevant questions scholars should ask and provides referenced resources on specific methods that help to align theoretical concepts with different high resolution methodological approaches. For illustration purposes, we apply each of these steps to a hypothetical study of team coordination processes.

-----Insert Table 4 here-----

Identification of research questions focusing on team dynamics. First, researchers will need to ask a research question that identifies how knowledge about team dynamics is currently under-developed or incomplete. As our review of high resolution methods has shown, empirical studies that unpack the actual dynamics at the core of team phenomena are still very rare, so there are lots of unanswered questions. An exemplary research question could be, “How do coordination patterns affect team effectiveness?” (Table 4, column three). To answer this question, researchers need to estimate the phenomenon time span. In other words, over what time period does the focal phenomenon occur and fluctuate in meaningful ways? Answering this question will help to determine the temporal granularity at which the team phenomenon should be measured and answer *how* and at what time intervals measurements need to be taken. Overall, this step taps into the parts-versus-whole issue which is crucial for selecting the appropriate high resolution measurement approach.

For example, imagine a team of researchers who want to understand how team coordination occurs within a surgical team, and whether team coordination has any impact on adverse patient errors. In terms of time span, based on unstructured observations (from having access to their local hospital) and based on the extant literature (Kolbe & Boos, 2019), the researchers know that team coordination behavior (assisting others, monitoring the patient) can unfold and change during a single operation. In terms of temporal theory, the researchers thus decide to adopt an episodic lens and to focus on coordination during surgical operations as the central performance episode. Based on this decision, the researchers need to decide how they want to measure coordination. That is, they need to decide when (i.e., how often) and how to measure (i.e., selecting the right high resolution method) coordination behaviors that occur during the operation.

High resolution data collection and management. The researchers now need to collect and manage high resolution data to answer their research question. When they have an idea about the time span over which the phenomenon unfolds as a whole (e.g., within seconds, days, or years?), they have a rough estimate for the observation period that is necessary for data collection. As an initial point of reference for estimation, researchers can use Table 1 which provides time frames for some team phenomena within field contexts and industries. Of note, it is not always easy to estimate the phenomenon time span as there is a dearth of empirical research that gives concrete estimates about such time frames (for exceptions see Delice, Rousseau, & Feitosa, 2019). Furthermore, it is important to select relevant time intervals for collecting repeated measures. In our example, the researchers consult the literature (e.g., Waller & Kaplan, 2016, see also Table 1) which indicates that coordination dynamics in surgical teams have been measured multiple times per minute.

Alternatively, the researchers could have determined the temporal resolution by using Table 2: Knowing that the phenomenon time span is operationalized as a 30-minute episode (which is the average length of operations in their local hospital), this would mean to use a high resolution method that repeatedly samples the phenomenon with at least a minute (or even second) precision. The researchers consider that they want to measure coordination behaviors in ten-second intervals by tallying coordination behaviors in these intervals throughout the medical operation.

Following this, it is important to select an appropriate high resolution method. There are a variety of high resolution approaches from which the researchers can select. For example, researchers can use video-recordings (Waller & Kaplan, 2016), use text data from team transcripts (e.g., Driskell et al., 2017), emails or electronic-traces of team interactions (Braun, Kuljanin, & DeShon, 2018), access archival records (cf., Braun et al., 2018; usually used in the context of sports teams, this type of data is easily accessible via websites: e.g., www.basketball-reference.com or www.nhl.com), or utilize sociometric badges (Kim, McFee, Olguin, Waber, & Pentland, 2012)[3]. As we have outlined in Table 2, some of these methods are better suited for phenomena that have a short time span (e.g., video-data, instant messaging, or sociometric badges), while other high resolution methods are better suited for team phenomena that have a larger time span (e.g., archival data). In our hypothetical research study, the researchers have the opportunity to analyze an archive of video-recorded anesthesia inductions that have been collected from the local hospital as part of a training program. The hospital grants the researchers access to this dataset for research purposes. In return, the hospital hopes to receive insights on how patient safety during medical procedures can be improved.

[3] This list may not be exhaustive.

Once the high resolution method is selected, the researchers need to decide how to manage the complex dataset. In essence, this means to decide how the 'raw data' (i.e., video-records) can be transformed into meaningful (and repeated, that is, time-logged) quantitative measures of the focal team phenomenon. Depending on the selected high resolution methods (i.e., video observations, chat logs/transcripts, archival data etc.), data transformation procedures are more or less evolved − both in terms of efforts, that is, manual versus automatic transformations, and in terms of operationalizing different team phenomena. For example, when using a video/observational approach, there is a selection of various manual coding tools (focusing on various team phenomena). Deciding which tools to use should be mainly guided by the research question and which phenomena researchers would like to understand. In this respect, Brauner, Boos, and Kolbe (2018) have organized over 20 coding tools (including an annotated Appendix of an additional 48 coding schemes) into different areas of team phenomena (general group processes, conflict, coordination, cognition, etc.). They also provide decision criteria for selection (Brauner et al., 2018): For example, is the tool available in different languages, are there online versus paper versions, where is the tool typically applied (lab or field research), practical aspects such as resources, training manuals and technical requirements, tool quality in terms of reliability and validity, and existing publications. This information is key in weighing various pros (e.g., reliability and validity data about a specific coding tool, application in many or few studies) and cons (e.g., complexity: Is the tool so complex that it takes 2 hours to code 1 minute, is the training manual only available in French?). Furthermore, Waller and Kaplan (2016) provided some guidance for researchers who want to develop their own coding schemes.

While progress is on the horizon to use automatic or machine-learning for obtaining meaningful team measures from high resolution data (e.g., Bonito & Keyton, 2018; Lehmann-Willenbrock, Hung, & Keyton, 2017), the majority of video-based approaches still relies on trained human observers who need to have sufficient context knowledge, cognitive capabilities, and understanding of the focal team process. Moreover, while behavioral and verbal processes are more easily observable for external observers, cognitive and affective team processes may be less visible for external observers (Carter et al., 2018). Importantly, in order to understand team dynamics, it is crucial that the selected high resolution method also repeatedly time stamps the focal phenomenon. For example, when using archival sports data, the researcher needs to know at what year, month or week the teams played in a game. This is essential to be able to draw an accurate picture of the team's developments over time. As another example, when coding team interactions from video data, the coding tool should not only code but also time-stamp occurrences of team coordination behaviors. When using chat data, the researchers need to pay attention to get information about the time points that messages have been sent.

To increase the rigor of a research design, we recommend linking data from non-traditional methods with other methods (e.g., self-report team measures are very well suited to assess latent or perceptual team phenomena that are harder to capture with non-traditional methods). That is, researchers are well advised to use multiple methods in their study designs whenever possible. At the same time, reviewers should also understand that field projects can extensively limit a researcher's ability to use the most rigorous measures (e.g., a 20-item survey measure for a single construct may be difficult to use in the wild). In our example study, the researchers had access to team performance measures (i.e., an experienced staff member rated clinical team effectiveness with an established checklist that covered adverse patient outcomes) but could not implement additional self-report measures after the videotaped operations.

If a researcher decides to collect electronic data, archival records, or text data, and aims to transform the data into meaningful team phenomena, we recommend consulting the exemplary studies presented in Table 3. For example, Riedl and Wooley (2017) used raw data (electronic logs) from crowd-working teams and transformed them into indicators of team process measures. Others have used archival data from sports teams to measure team coordination (Halevy et al., 2012; Swaab, Schaerer, Anicich, Ronay, & Galinsky, 2014). If the researchers have some sort of text data (e.g., virtual chat logs, email transcripts), they could rely on various tutorials that explain how to use automatic text analytic approaches (Banks, Woznyj, Wesslen, & Ross, 2018; Bonito & Keyton, 2018; Short, McKenny, & Reid, 2018; Gonzales, Hancock, & Pennebaker, 2010). While text-analytic approaches are more advanced with respect to the automation of data transformation, they may still involve transcription efforts (for example, if the researchers had decided to transcribe video-recorded communication, e.g., Bonito & Keyton, 2018) and close collaboration with computer scientists (Büngeler et al., 2016). If the researchers had decided to use wearables for data collection, we advise them to have a look at Chaffin et al. (2017) who systematically evaluated the validity of different wearable sensor methods (e.g., microphones, Bluetooth) for capturing various team phenomena (e.g., boundary spanning behaviors, emergent leadership) in different study settings (lab vs. field). Scientific advancement will be facilitated when reviewers and editors, in their position as gatekeepers, acknowledge that research "in the wild" often has exploratory elements and a certain degree of messiness. Accordingly, an open mindset toward novel approaches is necessary to allow expanding our understanding of team process dynamics.

In our hypothetical study, the researchers (who decided to use video-recorded data) now consults the aforementioned overview of coding schemes from Brauner et al. (2018) and selected Co-ACT (i.e., a coding scheme to measure coordination in acute care teams). This allows them to capture different types of micro-coordination behaviors. Furthermore, the researchers decided to use software-support for coding the videos (after reviewing Klonek, Meinecke, Hay, & Parker, 2019; Lehmann-Willenbrock & Allen, 2018; Waller & Kaplan, 2018) which allows them to save time-stamps and the sequential order of the micro-coordination behaviors.

Data analysis. In the third step, the researchers of our exemplary study now have a completely coded dataset of time-stamped team coordination behaviors (that were displayed throughout an episode of anesthesia inductions). Going back to their initial questions, the researchers wanted to know how team coordination behaviors occured in these performance episodes and how these dynamics impacted team outcomes (including adverse patient errors). Statistical approaches should help the researchers in answering these questions about temporal patterns or whether temporal team patterns show a relationship with other variables (e.g., team outcomes). There are a number of statistical guides available that researchers could use as a starting point to detect non-random temporal patterns (see Table 4, demos and tutorials). A helpful distinction in selecting the appropriate analytical approaches is to understand whether they rely on time-stamped categorical measures (e.g., Ballard et al., 2008; Herndon & Lewis, 2015; Klonek, Quera, Burba, & Kauffeld, 2016; Waller & Kaplan, 2018) or whether they rely on time-stamped continuous measures (e.g., Collins, Gibson, Quigley, & Parker, 2016). For example, statistical methods like sequential analyses, relational event modeling, or pattern analyses all rely on analyzing the temporal order of different codes that describe how team interactions unfold as discrete categorical events over time (they also have a tradition to be used in research focusing on micro-dynamics). In our hypothetical example, time-stamped codes that reflect temporal coordination would be: [01:20] “talking to the room”, [01:35] “monitoring”, [01:40] “providing assistance”. Other examples (from using electronic data) for time-stamped categorical data would be [00:01] “A sends a message to B”, [00:05] “C sends a message to A” (see Leenders et al., 2016; Schecter et al., 2017). It is also possible to use these methods to study archival data focusing on larger time spans (e.g., [Month1] "project A", [Month2] "project B", [Month3] "project D"; for related applications see Biemann & Wolf, 2009).

In contrast, statistical methods such as growth curve modeling (Collins et al., 2016) or multi-level modeling (Hedecker & Gibbons, 2006) mostly build on repeated continuous measures and use statistical approaches that extend regression-type approaches (which most management and organizational behavior researchers are more familiar with).

In terms of statistical software solutions, the researchers can rely on detailed tutorials for analyzing categorical data (e.g., for sequential analytic approaches, see Bakeman & Quera, 2011, Biemann & Datta, 2014; Pilny et al., 2016; for pattern analytic approaches, see Magnusson, 2000; for comparisons of analytical approaches and available software options, see Lehmann-Willenbrock & Allen, 2018) as well as continuous team measures (e.g., for using growth curve modeling, see Collins et al., 2016; for using multi-level modeling, see Hedecker & Gibbons, 2006).

Because the researcher in our hypothetical study used time-stamped codes of coordination micro-behaviors, they select one of the various options for analyzing categorical team process measures. Unfortunately, they are unsure whether to select sequential analyses (Bakeman & Quera, 2011), pattern analyses (Ballard et al., 2008) or relational event modeling (e.g., Pilny et al., 2016). If the researchers were interested in the relational communication structures (i.e., the tendencies of team members to reciprocate messages from others), they could use methods like relational event modeling (Pilny et al., 2016). If the researchers were interested to which extent teams synchronize their interdependent activities in a more scripted versus a temporally flexible (or more spontaneous) way, they could use methods like pattern analyses (e.g., Ballard et al., 2008; Magnusson, 2018). Interaction patterns are defined as "a set of molecular actions that […] repeatedly co-occur" (Stachowski et al., 2009, p. 1537). The repeated co-occurrences of activities means that certain behaviors happen either simultaneously or in close temporal proximity. When teams exhibit strong patterns, they typically adhere more to strict rules and procedures or scripts, much like following a recipe: First team member A does X, then B does Y, etc. In contrast, teams exhibiting weak patterns are considered to be flexible and agile in their activities.

However, the researchers in our hypothetical example decide to unpack the systematic sequencing of effective team coordination. Sequential associations can be positive (A is likely to be followed by B) or negative (A likely suppresses B). Our researchers wonder whether teams that differently sequence their coordination behaviors (i.e., monitoring and speaking up during the procedure) also show better performance. Hence, they decide to analyze their dataset with sequential analyses (using tutorials provided by Bakeman & Quera, 2011; Klonek et al., 2016). Since the researchers had an external rating of team effectiveness, the researchers divide their sample into teams that showed high performance versus teams that showed low performance. In the next step, they test whether those two groups showed different sequential patterns. Using software provided in the tutorials (e.g. Klonek et al., 2015), they create time-lagged matrices and calculate statistical association indices for each team. When comparing the high with the low-performing teams, they find that high-performing teams showed a higher probability for monitoring-speaking up sequences, whereas low-performing did not show these behavioral sequences[4].

Of note, sequential analyses are not restricted to phenomenon of small time spans. Researchers who want to focus on team development could use sequential analyses for other types of high resolution data as well (i.e., archival data). For example, when studying how changes in team membership occur over time, researchers can identify team member exit

[4] For an actual study that used a similar approach and reported these results, see Kolbe et al. (2014).

patterns and relate these patterns to team performance data (for more details, see Biemann & Wolf, 2009; Herndon & Lewis, 2015).

Interpretation of results. In the final step, the researchers need to interpret their results. In some cases, interpretation of results may be straightforward. In particular, when following a deductive hypothesis-driven approach (i.e., validating a hypothesized association) and relying on methodological guidelines that specify benchmarks for measurement fit and statistical significance.

In our example, the researchers have used coded team coordination (from video-recordings) and this approach involved transformation of qualitative data into quantitative data (through a coding schemes). Since this approach overlaps with mixed-methods research (Gibson, 2017), it also allows more discovery-oriented research and the use of abductive reasoning (Behfar & Okhuysen, 2018) which may be key in discovering new knowledge about team dynamics.

Mixed-methods. As noted above, some high resolution approaches (i.e., video recordings, the use of text or email transcripts) rely on transformation of qualitative data into quantitative data (i.e., numbers/categories representing variables). Hence, researchers can apply a mixed-methods approach (Gibson, 2017). The strength of mixed-method research is that researchers can use both quantitative and qualitative data to triangulate their concepts, to provide richer descriptions of the focal phenomenon, and to extract novel phenomena. By using a mixed-methods approach, researchers could first analyze a subset of data using a qualitative lens (qualitative data is mostly unstructured data such as video-recordings, field observations, or written communication) that will help them to extract meaningful patterns (e.g., using a micro-temporal lens, patterns could be re-occurring communication sequences). In a second step, researchers can select from the various manual or (semi-automatic) data transformation methods (Table 4) and use analytical methods to test statistical associations of these observed dynamics.

Researchers can also apply mixed methods in the reverse order (i.e., quantitative followed by qualitative analytical techniques). We have not seen many studies that went back to qualitative data to understand the meaning of certain patterns (Hoogeboom & Wilderom, 2019; Wang et al., 2018). For example, after having identified meaningful patterns (e.g., are there sequences in the performance episode during which team members disagree versus agree after a solution was proposed?), researchers can investigate what happened immediately before or after these focal sequences. Researchers can also use this mixed-methods to further validate their hypotheses. To provide an example, Wang et al. (2018) developed competing hypotheses about the effect of shared versus unshared laughter for crews during a simulated flight. Using quantitative methods, the authors found that shared laughter was detrimental for team performance. Following this, the authors used qualitative methods to understand what happened during laughter episodes. This in-depth analysis helped them to extend their arguments that shared laughter shifted the task focus of the team towards a "play focus". That is, shared laughter episodes showed that teams engaged in playful conversations and stopped to focus on important task aspects. In sum, this approach was insightful to understand the nature of counter-intuitive findings.

Abductive reasoning. Abductive research describes a middle-ground approach between theory testing (deductive, typically quantitative approaches) and theory development (inductive, typically qualitative approaches; e.g., Bamberger, 2016). Abductive approaches apply when researchers are dealing with anomalies and surprising finding (Bamberger, 2016; Behfar & Okhuysen, 2018). This type of research is more discovery-oriented (and may fit well with novel journals such as the *Academy of Management Discoveries*). For example, Bowers et al. (1998) used sequential analysis in an exploratory way and concluded that the "analysis provided hypotheses about the nature of effective team process that would not have been revealed by using simple frequency counts" (p. 677). This quote illustrates that researchers shifted their mindset from a static team research lens towards a process dynamics lens. This abductive reasoning can also be found in some reflection reports from researchers who used pattern analyses. These researchers "were disappointed to find virtually no significant difference" when they compared static process measures (i.e., frequencies) between high and low-performing teams but "found almost all the measures to be significantly different" when using an interaction pattern recognition program (Ballard et al., 2008, p. 328; see also Waller & Kaplan, 2018).

It is noteworthy that some of the reviewed studies that focused on interaction patterns presented their research in a hypothetico-deductive fashion (i.e., using a priori hypotheses) in the published manuscripts (e.g. Zijlstra et al, 2012; Lei et al., 2011) — likely in order to adapt to common expectations of reviewers and editors who are less open to the more discovery-oriented and abductive reasoning approaches described in the above quote from Ballard et al. (2008). The same likely applies to many other published studies using either sequential or pattern analysis. It is possible that this perspective has already changed as some journals (e.g., *Academy of Management Discoveries*) are becoming more open towards abductive reasoning approaches and give researchers a chance to describe (unsuccessful) research endeavors (Bamberger & Ang, 2016), report surprising and unexpected results, and provide arguments and possible reasons for unexpected findings in order to tell a coherent story. Nevertheless, it probably still requires a joint effort of authors and reviewers until explorative approaches are truly established in a wider range of top-tier journals. That is, authors need to be more transparent about their explorative analysis trying to "find something in the data", and reviewers need to be more accepting of the possibly that existing theory can be advanced without a priori assumptions.

In conclusion, we hope that our review and "how to guide" will encourage researchers to "go wild" and use non-traditional high resolution methods to study dynamic phenomena in real teams. Our conceptual framework can serve as a starting point for theorizing and for aligning theory and methods. Ultimately, we are confident that increasing the variety of methods to study teams in the field will contribute to advancing our knowledge about team process dynamics.

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Table 1

Illustrative field studies using high resolution methods

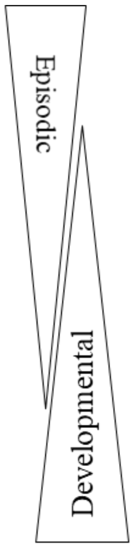
Illustrative study	Temporal theory	Focal team phenomenon	Operationalization of phenomenon time span[1]	Number of repeated measurements[2]	Indicator of temporal resolution [3]	High resolution method	Industry	Context	Team sample[4]	Context for sampling of processes
Kolbe et al. (2014)	Episodic	Team coordination	21.5 min	$N_t = 387$ observations [per operation]	Minute ($f_{min} = 18$)	Video	Healthcare	Medical teams (action teams)	$N_k = 28$	Anesthesia induction
Lei et al. (2016)	Episodic	Interaction patterns	70.72 min.	$N_t = 462$ observations [per team]	Minute ($f_{min} = 6.5$)	Video	Aviation	Airline flight crews (action teams)	$N_k = 11$	Cockpit flight (Multi-episodes, simulation)
Schecter et al. (2017)	Episodic	Communication mechanisms	60 min.	$N_t = 651$ observations [per team]	Minute ($f_{min} = 10.8$)	Chat-data	Military	NATO officers (action teams/ virtual teams)	$N_k = 55$	Strategy (simulation)
Stachowski, et al. (2009)	Episodic	Interaction patterns	15 min.	$N_t = 35$ observations [per team]	Minute ($f_{min} = 2.3$)	Video	Energy	Nuclear power plant crews (action teams)	$N_k = 14$	Crisis management (high-fidelity simulation)
Riedl & Wooley (2017)	Develop.	Burstiness (of activities), Communication (info. diversity)	10 days	$N_t = 33.5$ observations [per team]	Day ($f_{day} = 3.3$)	Electronic logs (online platform)	Crowd-sourcing	Software programing (virtual teams)	$N_k = 52$	10-day online competition

Kim et al. (2012)*	Develop.	Team coordination	7 days	$N_t = 7$ observations / [per team]	Week ($f_{week} = 7$)	Sociometric badges	Engineering	Multicultural engineering teams	$N_k = 1$	Life-cycle of designing/ building a machine
Grijalva et al. (2019)	Develop.	Team coordination	~ 6 months	$N_t = 82$ observations [per team]	Week ($f_{week} = 3.6$)	Archival data (website)	Sports	Basketball (sport/action teams)	$N_k = 30$	Multiple games per team (one season)
Stuart & Moore (2017)	Develop.	Team adaptive processes	24 months	$N_t = $ ~416 observations [per team]	Week ($f_{week} = 4$)	Archival data (website)	Sports	Ice-hockey (sport/action teams)	$N_k = 30$	Multiple games per team (two seasons)
Paletz et al. (2016)	Episodic and Develop.	Conflict management	11.42 hours; 90 days	$N_t = 6{,}168$ observations [per team]	Minute ($f_{min} = 8.9$)	Video	Aeronautics Science	Multidisciplinary Team (extreme teams)	$N_k = 2$	Informal, task-relevant conversations during Mars trip (Multiple episodes)

Notes. [1]Operationalization of the phenomenon's time span: Most researchers used the length of a performance episode within the work context of the teams, such as length of sports game, length of surgical operations, flight simulation etc.; when applicable, we calculated the average. [2] N_t = Number of repeated measurements that were captured within the time span that was selected to observe the whole phenomenon.[3]To estimate measurement resolution, we divided N_t by the time in column four. $f_{min}/f_{hour}/f_{day}/f_{week}$= sampling rate indicating how many measurements were collected per time minute/hour/day/week etc.; we selected time scales so that measurement resolution was > 1 per time-unit (seconds, minutes etc.). For example, $f_{week} = 3.15$ (i.e., collection of 3.15 measurements per week, cf., Grijalva et al., 2019) could capture changes occurring within a week. However, f_{week}= 3.15 would not allow to capture changes occurring in a day as $f_{day} = 0.45$ is smaller than 1. [4] N_k = number of teams; *We refer to the second study presented in this paper.

Table 2

Example phenomena of increasing time spans and their alignment with various high resolution methods

Temporal theory	**Example phenomenon**	**Phenomenon time span (whole)[a]**	**Clock time measurement (When should the ‘parts’ be measured)**	**Possible high resolution methods to collect data**
	Emotional mimicry	Within 1 Second*	Milliseconds	Physiological measures (heart rate, neuroscience)
	Emotional contagion	Seconds to Minutes**	Seconds or Minutes	Video-data, instant messaging, socio-metric badges
			Hours	
	Team negative affect	Weeks to Months***	Days	Electronic activities in virtual teams or crowd-sourcing competitions
	Team negative climate		Weeks	Written communication (e.g., e-mails)
	Collective burnout	Over multiple Years****	Months	Archival records (e.g., NBA sports records of multiple games)
			Years	Historical team records,yearly performance measures from HR records

Note. [a] Phenomenon time span was estimated based on the available literature (see references below) and represent ‘best guesses’ of relevant time spans under which these phenomena most likely unfold: * Dimberg, & Thunberg (1998), ** Barsade, (2002), *** Paulsen et al. (2016), **** González-Morales, Peiró, Rodríguez, & Bliese, (2012).

Table 3

Three approaches for using high resolution methods

Approach	**Treatment of process**	**Research questions**
Static (LePine et al., 2008) *Core assumption*: "Teams differ with respect to their processes which affect their effectiveness."	Variations of variables between teams	• Do differences between teams in the amount of teamwork behavior explain team performance? • Do teams with different levels of coordination behavior show differences in team effectiveness? (Schmutz et al., 2015) • Do teams that exhibit more planning behavior also show higher team productivity? (Kauffeld & Lehmann-Willenbrock, 2012)
Multiphase or socio-technical[1,2] (e.g., Gersick, 1988; Marks et al., 2001; Rousseau et al, 2006) *Core assumption*: "Teams must execute different processes at different times, depending on task demands"	Temporal variations of one time variable (or one dynamic task feature) and one team process variable over time	• How do dynamic changes in task conditions affect the level of teamwork behaviors? • Does in-action team reflexivity increase over the phases of a team performance episode? (Schmutz et al., 2018) • How do support team leadership behaviors differently stimulate team member voice in action versus transition phases? (Farh & Chen, 2018) • How do adaptive crew behaviors (e.g., collecting information and task distribution) vary with changes in dynamic task demands (routine vs. non-routine situations)? • Do crisis management teams spend more/less time in different team phases (i.e., structuring, information-sharing, decision-making) (Uitdewilligen & Waller, 2018)? • How does teamwork change from routine to non-routine phases? (David & Schragen, 2018) • How is team coordination in online teams affected by different levels of task interdependence? (Riedl & Woolley, 2017)
Process dynamics[1] (e.g., McGrath & Tschan, 2004; Pilny et al., 2016) *Core assumption*: "Team processes can be characterized by systematic interaction patterns"	Temporal variations of at least two team variables over time	• How does the occurrence of one teamwork behavior (e.g., workload sharing) affect another behavior (e.g., conflict) over time (within a single performance but also as the team develops)? • How do effective versus ineffective teams differ in their temporally patterned team interactions (Stachowski et al., 2009)? • Do teams during a surgical operation show systematic sequential behavior patterns? (Kolbe et al., 2014) • How do temporal variations in team coordination affect temporal variations in team performance? How do team-member traits emerge and damage team coordination as the team develops (Grijalva et al., 2019)?

Note: [1]Applicable to team episodic and team development model, [2]predominantly used with episodic models

Table 4

"How to" guide for adopting high resolution methods

Step	**Key questions to be addressed**	**Suggestions and guidelines in answering key questions, exemplary answers, and further resources of help**
(1) Identification of research questions	How is knowledge about team dynamics under-developed or incomplete?	See Table 3 for possible research questions • Example for a potential research question: "How do effective versus ineffective teams differ in their temporal coordination patterns?"
	What is the time span of the "whole" phenomenon? How should the team phenomenon be measured? What temporal theory is most relevant? When should measures be taken?	See Table 2 for a *phenomenon's time span* • Example for operationalizing *phenomenon's time spans*: "For surgical teams, coordination behavior (assisting others, monitoring the patient) unfolds and changes during a single operation. An operation takes about 30 minutes." • Example for *how to measure*: "The researchers consider coding coordination behaviors that occur during a single performance episode (i.e., an operation)." See Table 2 for *levels of temporal theory* • Example: "Since teams are observed within a surgical episode for which performance is available, the researchers take an episodic theory lens and use the operation as a way to operationalize the performance episodes." *Further resources:* Understanding the role of time (Vantilborgh, Hofmans, Judge, 2018), multi-level theory (Klein & Kozlowski, 2000), time episodic models (Ishak & Ballard, 2012; Marks et al., 2000)
(2) Data Collection & Management	What are relevant time interval(s) for collecting the "parts" of the "whole" phenomenon?	See Table 1, column *indicators of temporal resolution*, for examples of time intervals • Example: "The literature in Table 1 indicates that dynamic coordination should be measured multiple times per minute. The researchers consider to time-sample the phenomenon by tallying team coordination behaviors in 10-sec intervals." *Further resources:* What, when, and how to measure some team phenomena see Delice, Rousseau, & Feitosa (2019)
	How will high resolution data be collected (e.g., audio, video-, chat logs/transcripts, archival data, wearables)?	When you know the phenomenon's time span, use Table 2 to select a high resolution approach that fits best: • Example: "With a relatively short time span of the team coordination phenomenon, the researchers decide to access an archive of video-recorded surgical operations." Further resources for handling data from different high resolution approaches: Key considerations for collecting *video-recordings of teams,* see Waller & Kaplan (2018) For examples of collecting data using *live observation*, see Farh & Chen (2018), Liu et al. (2019)

		For collecting *team lexical/text data*, see Driskell et al. (2017), Riedl & Wooley (2017) For tutorials on accessing and processing *big data on team dynamics* (e.g., sports archives, email corpuses, computer games) see Braun et al. (2018). Online archives: www.basketball-reference.com; www.nhl.com; https://developer.riotgames.com ; https://x-culture.org/for-researchers/data/ For demonstrative case studies and guidelines using *sociometric sensors/wearables*, see Chaffin et al. (2017), Kim et al. (2012), Santaro et al. (2015) For helpful suggestions on aligning *dynamic team constructs* with *non-traditional measurements*, see Luciano et al. (2018)
	How will "raw data" be transformed into a dynamic measure of the phenomenon?	Depending on how "raw data" is collected, there are different ways to transform (or re-code) *raw data* into (repeated) measures of *team phenomena.* Further resources: When transforming video team data/live observations, researchers can use *manual team coding schemes*: For an overview of 24 coding instruments (to assess group processes, conflict, coordination, team cognition etc.), see Brauner et al. (2018); for software support in transforming video-recordings: Klonek, Meinecke, Hay & Parker (2019); Lehmann-Willenbrock & Allen (2018). Free software tools for coding video/audio data: https://cat.ctwd.com.au For examples how to transform *archival* sport team data into "team phenomena", see Halevy et al. (2012) For examples/overviews how to transform electronic data from *online teams*, see Riedl & Wooley (2017), Gibson (2018) For overviews/tutorials how to use *automatic text analytic approaches* to transform text into team constructs, see Banks et al. (2018), Bonito & Keyton (2018), Short et al. (2018), Gonzales et al. (2010). Available Tools for "Computer-Aided Text Analysis": http://www.amckenny.com/CATScanner/ http://liwc.wpengine.com/ For construct validity of data from wearables with surveys (in lab and field contexts), see Chaffin et al. (2017) • Example: "The researchers code the videos with Co-Act (a validated scheme that captures team coordination). Furthermore, they use free software-support which allows them to time-log the on- and offset times of coordination activities."
(3) Data Analysis	Can we detect temporal patterns? How to determine if	Demos / tutorials: When using *categorical measures*:

	these patterns are statistically significant? Is there a relationship between temporal patterns and team outcomes (e.g., team performance or team efficacy)?	*Sequential analyses*: Bakeman & Quera (2011), Herndon & Lewis, (2015), Klonek et al. (2016) *Relational event modeling:* Pilny et al. (2016), Schecter et al. (2017), Quintane, Conaldi, Tonatello, & Lomi (2014) *Pattern analysis:* Ballard et al. (2008), Lehmann-Willenbrock & Allen (2018), Magnusson (2018) When using *continuous measures*: *Growth curve modeling:* Collins et al. (2016), Quigley, Collins, Gibson & Parker (2018) *Multi-level modeling:* Hedeker & Gibbons (2006) • Example: “In terms of temporal patterns, the researchers analyze and extract the strength of association for coded micro-sequences using sequential analyses (for each surgery). Based on objective team performance data (i.e., patient recovery time), they test if the strengths of these micro-sequential associations are different for high- versus low-performing teams.”
(4) Interpretation of Results	*Abductive reasoning*: Are there different patterns for high- vs. low-performing teams? *Mixed-methods approach*: What do these patterns mean?	*Further resources:* For *abductive reasoning*, see Behfar & Okhuysen (2018) For using *mixed-methods*, see Gibson (2017) Example: “The researchers cannot find a significant relationship between the number of sequential coordination patterns and team performance. They select a subsample of three high- and three low-performing teams and decide to watch the video-recording segments for those time points during which coordination sequences occurred (e.g., assisting-followed by-monitoring) and try to discover qualitative differences in these sequences. For similar examples of abductive reasoning with high- versus low-performing teams, see Hoogeboom & Wilderom (2019)

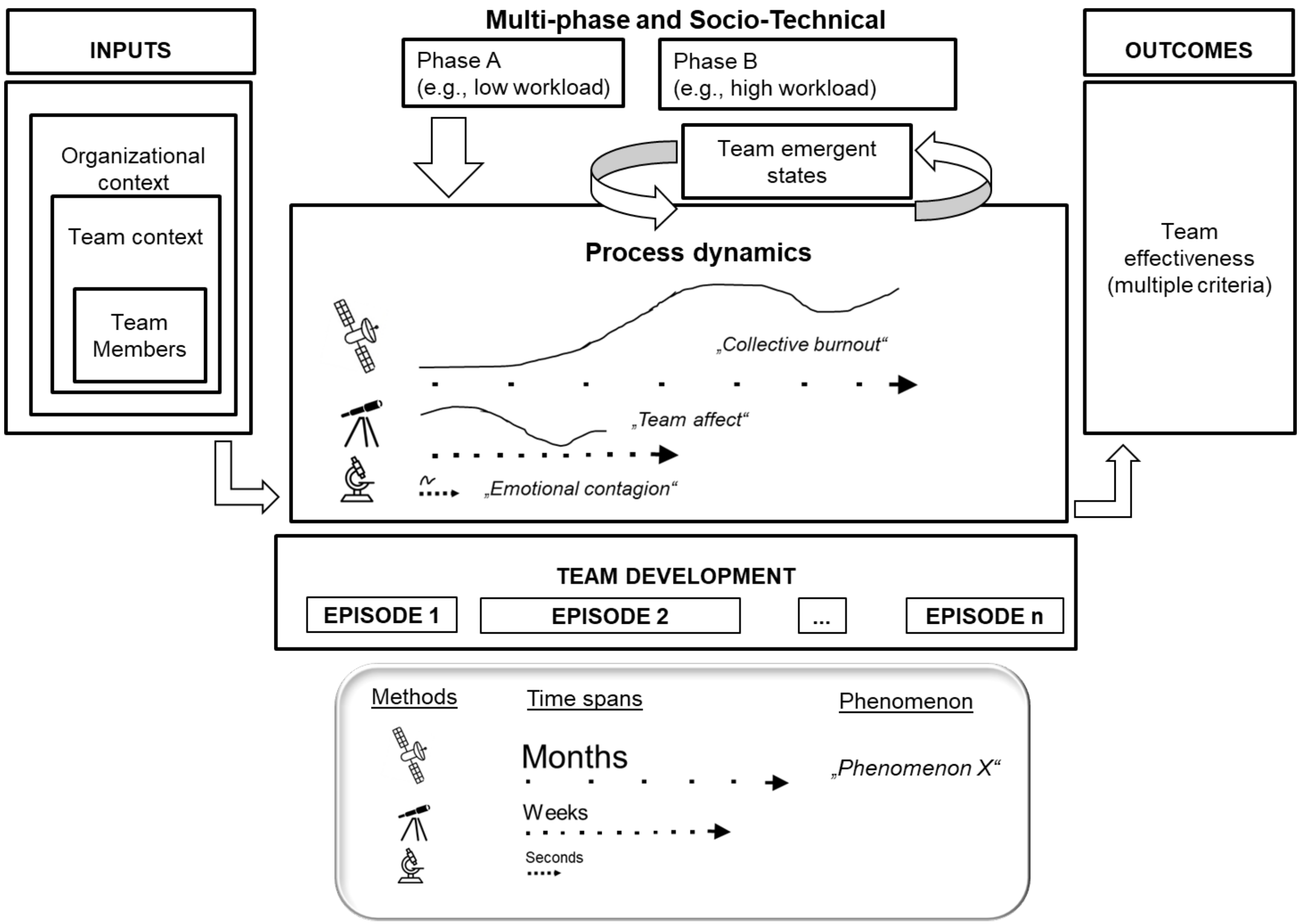


Figure 1. A temporal framework to understand team dynamics with high resolution