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Looking to the Middle of the Qualitative-Quantitative Spectrum for Integrated Mixed Methods

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Abstract
Substantially advancing the study of teams will require a new research paradigm complete with methods capable of capturing the complex, dynamic process of teamwork. In this paper, we suggest studying teams with an integrated mixed methods approach (i.e., methods defined by an interconnected mix of quantitative and qualitative characteristics) can help address current methodological shortcomings of our science by promoting sufficiently contextualized research. Through a review of methods, we highlight exemplars of integrated mixed methods that have the potential to be more widely adopted; namely, interaction analysis, content analysis, cluster analysis, state space grids, and agent-based modeling.

Keywords
interaction analysis, content analysis, cluster analysis, state space grids, agent-based modeling

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From its roots in social psychology to the relative explosion across disciplines, teams research utilizes a wide variety of quantitative and qualitative approaches to study team dynamics (Mathieu et al., 2018). However, teams researchers have acknowledged that a new, integrated research paradigm is required to advance our understanding—a paradigm capable of capturing the complex, dynamic nature of teamwork through a combination of quantitative and qualitative methodologies (Mathieu et al., 2008). As individuals work in teams, social dynamics and emergent properties interact with team processes and endure over time to impact future team performance (Waller et al., 2016). This is a complex process, not easily captured in static measurements or data points (Humphrey & Aime, 2014). As suggested by the notion of requisite complexity, complex processes require complex research methods (Boisot & McKelvey, 2011), and team science could continue to grow if we address these complexities via a methodological shift. To support the move toward a more comprehensive research paradigm, we present a review of methods that may be uniquely suited to studying team-level phenomena—integrated mixed methods approaches. In this paper, we introduce the concept of integrated mixed methods, highlight methods that address requisite levels of complexity for studying team science, and demonstrate how these methods are strategically advantageous and uniquely suited to uncover the dynamic and complex nature of team-level phenomena.

As others have noted, neither a completely qualitative nor completely quantitative research approach is alone sufficient for understanding most team characteristics, as both approaches have unique benefits and drawbacks (Bell et al., 2018). Qualitative research can provide a rich description of the role of context and of group and team[1] processes, allowing researchers to gain a more complete conceptualization of how phenomena occur (Bell et al., 2018; Kozlowski, 2015). Qualitative research is vital for developing and extending theory and can be used when research is in its nascent stages or when quantitative measurements are unavailable or insufficient (Edmondson & McManus, 2007). However, it can be challenging for researchers to gain the in-depth and sustained access to participants needed for qualitative data collection, or to spend months in the field over the multiple timepoints necessary to gather and analyze the data. Furthermore, it can be difficult to judge the relative importance of the components of a phenomenon and their relationship to other components without some means of quantification. Additionally, qualitative data often cannot be generalized across contexts or be easily distilled into statistical results that rest upon assumptions such as normal distributions and specific (albeit socially constructed) significance levels (Ziliak & McCloskey, 2008).

Quantitative research approaches generally excel where qualitative methodologies falter; some approaches may be less time consuming, allow for statistical control of extraneous variables, and can be more easily accepted in some academic and professional settings (Johnson & Onwuegbuzie, 2004), particularly for theoretically mature topics (Edmondson & McManus, 2007). Although they allow for inferences about the data to be made, quantitative methods are often unable to sufficiently explicate the contexts within which phenomena occur (Bell et al., 2018). Moreover, there are other issues with quantitative methodologies specifically linked to the nature of teams research. For example, Humphrey and Aime (2014) claim that overreliance on survey-based research requires researchers to include new items and scales for each construct of interest, as well as garner input from several, if not all, team members. This approach may discourage the holistic evaluation of team dynamics and result in narrow theories and poor-quality research, as researchers may be inclined to include fewer constructs in what becomes a cumbersome survey (Humphrey & Aime, 2014). Additionally, scientists have noted the overreliance on linear statistical models, which impose obstacles for studying dynamics and are recommended for understanding more simple relationships between team constructs (Waller et al., 2016).

Considering the advantages and disadvantages of both, an approach that draws from the elements of both qualitative and quantitative methodologies may be beneficial for team dynamics research (Creswell, 2007; Mathieu et al., 2008). One such practice is triangulation, or adding multiple methods to understand the same phenomenon. Triangulation requires careful attention to ensure that the research scope, inferences drawn, and criteria for trustworthiness are aligned among methods employed. Triangulated methods may rest upon different underlying assumptions, epistemologies, and ontologies. Researchers practicing triangulation must be proficient in each method used to avoid inappropriate application, for example, using an inductive method to test a theory (Schoonenboom, 2018). Even when triangulation is executed correctly, the study results will not provide additional insights beyond what may be garnered from the qualitative and quantitative analyses. That is, with triangulation, the whole is equal to the sum of its parts.

An alternative to triangulation lies in *integrated mixed methods*. Researchers have called for methods which integrate "both qualitative and quantitative approaches in a single instrument, squeezing the advantages of both in a single technique" (Gobo, 2015, p. 331). Just as Bazeley (2016) drew attention to integrated mixed methods that exist in sociological research (e.g., geospatial referencing, qualitative comparative analysis), we do the same for an interdisciplinary audience of teams researchers. Specifically, we argue that the methods reviewed here are integrated mixed methods.

Integrated mixed methods exist at the center of the qualitative-quantitative spectrum. Rather than using a qualitative analysis to support quantitative analysis or vice versa, as in triangulation, integrated mixed methods may be thought of as a hybrid. Integrated mixed methods contain some steps or characteristics derived from the qualitative and quantitative literatures, but exist as a single, streamlined research approach. Because the qualitative and quantitative components of integrated mixed methods build off of one another, they may lead to insights otherwise inaccessible when applying triangulation. Altogether, our central aim is to postulate the relative advantages of integrated mixed methods and demonstrate how they may be applied in teams research to advance the science beyond what is possible with triangulated methods.

Mixed Method Analysis Types

Integrated mixed methods aim to capitalize on the benefits of both quantitative and qualitative research without succumbing to the shortcomings of either (Bell et al., 2018; Johnson & Onwuegbuzie, 2004). These methods can be used to capture emergent states and ongoing or retrospective team processes in a context-intact way, giving them a unique structural advantage for studying teams. We suggest that by using integrated mixed methods more often, team scientists can develop a more complete, richer picture of team states and processes, which may account for moment-to-moment behaviors and allow for more accurate diagnostics, new theoretical advancements, and better prediction.

There are many types of mixed methods approaches. Given the aim of this paper is to equip teams researchers with useful information regarding novel methodologies well-suited to teams, we choose to focus on methods that are underutilized in the teams literature and best fit our definition of integrated mixed methods. We omit other methods if they are already well-established in interdisciplinary teams research or if they are beyond our conceptualization of integrated mixed methods (e.g., comparative case analysis, structured behavioral observations, and the Delphi method; Bazeley, 2017; Gobo, 2015). For each of the methods we discuss (i.e., interaction analysis, content analysis, cluster analysis, state space grids, and agent-based modeling), we briefly describe the relevant research questions they may answer, the type of data required, and the potential benefits and drawbacks for using each.

Interaction Analysis

Interaction analysis is an interdisciplinary approach to understanding human communication, verbal and nonverbal, derived from qualitative methods such as ethnography and conversation analysis (Jordan & Henderson, 1995). There is a specific focus on the role of dialogue in interaction analysis, but pioneers of this method, such as Bales (1950), sought to differentiate it from related methods such as conversation analysis (Grossen, 2010; Marková, 2003, 2006). Video-recorded interactions are considered fundamental to conducting an interaction analysis, as textual data can easily be gleaned and analyzed from video recordings (Jordan & Henderson, 1995). Interaction analysis is based on several assumptions, including the assumption that expertise and knowledge are social constructs reflected in interpersonal interactions, rather than in intrapersonal cognition (Jordan & Henderson, 1995). Specifically, Grossen (2010) notes that "human thinking and action are conceived of as activities that are accomplished through language and social interactions" (p. 5). Thus, the unit of analysis is the conversation, with an additional focus on other social influences, such as tools that affect cognition or behavior (Grossen, 2010). For these reasons, interaction analysis sometimes includes so-called *collaborative viewing*, where the researcher and participant(s) watch a video-recorded interaction together, allowing the participant to stop the video and retrospectively explain their cognition. This discussion may also be coded, analyzed, and statistically reported as indicative of how the speaker formulates or reformulates their thoughts (Grossen, 2010; Jordan & Henderson, 1995). Due to the reliance on participants' experiences and self-described cognition, as well as the statistical results, we consider interaction analysis an integrated mixed method. To date, seven previous studies published in *Small Group Research* have used interaction analysis (Beck & Keyton, 2009; Hare, 2010; Kauffeld & Lehmann-Willenbrock, 2012; Keyton & Beck, 2010; Klonek et al., 2020; Löfstrand & Zakrisson, 2014; Paskewitz & Beck, 2018).

One popular form of interaction analysis is SYMLOG (which stands for System for the Multiple Level Observation of Groups; Bales & Cohen, 1979). SYMLOG is used to study individuals, dyads, and subgroups by considering three dimensions to interactions; namely, (1) dominance versus submissiveness, (2) friendliness versus unfriendliness, and (3) task versus emotional orientation (Keyton & Wall, 1989). Another common form of interaction analysis is Bales's (1950) interaction process analysis (IPA). IPA is a 12-code taxonomy of team verbal communication that consists of four groups, each containing three codes (Bales, 1950). The four groups are (1) positive social-emotional talk (e.g., shows solidarity/seems friendly), (2) negative social-emotional talk (e.g., shows tension or anxiety), (3) task-related questions (e.g., asks for opinions), and (4) task-related attempted answers (e.g., gives suggestions; Bales, 1950). Bales suggested that team verbal communication should contain about 50% more task-oriented communication than social-emotional talk. It is worth noting that several researchers have paired IPA with other forms of analyses. For example, Lehmann-Willenbrock et al. (2016) paired IPA with cluster analysis to study emergent roles for team members in meetings. Likewise, Peña and Hancock (2006) paired IPA with a content analysis to study text message communication in multiplayer video game teams; they found, in contrast to Bale's assertion, that there was significantly more social-emotional communication than task-oriented communication.

Benefits and drawbacks. Beck and Keyton (2009) state that interaction analysis is specifically useful for "examining messages sequentially to understand their relation to other messages" (p. 228). Interaction analysis may be implemented at the (1) individual, (2) dyadic, (3) subgroup, and (4) team levels. Broadly, interaction analysis is beneficial for examining interdependent team dynamics, as it relies on the understanding that cognition is displayed and developed in connection with others (Grossen, 2010). Interaction analysis is considered appropriate for temporal research and turn-taking research (Jordan & Henderson, 1995). The nature of video-recording and collaboratively viewing interpersonal interactions means that participants can highlight how their thoughts changed over time as a response to previous discussion or behavior, allowing for detailed temporal research. Likewise, turn-taking in conversations has been used to study group-level social interactions (Boswell et al., 2020). Interaction analysis is well-suited for turn-taking research, as observers can measure speaking length and conversational patterns in turn-taking throughout the course of a meeting. Turn-taking behavior may be useful for understanding the mechanics of how teams verbally coordinate and manage hierarchy; for example, research using interaction analysis has indicated that teams with higher reciprocity in turn-taking during team formation are more effective in non-routine work (Su et al., 2017; Zijlstra et al., 2012).

It is important to note that interaction analysis is not without drawbacks. For instance, it may be inappropriate for researchers interested in maintaining a view of cognition as an intraindividual process, as interaction analysis takes the perspective that cognition is developed in relation to others. In addition, the process of video-recording interactions in a population of interest carries the risk of unintentionally changing participants' behavior (Jordan & Henderson, 1995). Collaborative viewing, while potentially insightful, may be a time-consuming process for some research goals. The considerable time investment of collaborative viewing may be worthwhile for contexts in which team cognition changes rapidly, such as brainstorming or decision-making meetings. Researchers interested in interaction analysis, especially interaction analysis without collaborative viewing, should not be discouraged from using this method, as textual data is easy to obtain from audio or video-recorded interactions.

Exemplars from the literature. Interaction analysis has been used as a stand-alone method and paired with other methods to study teams. In one such example, teacher team meetings were recorded and analyzed to understand how team learning emerges (Zoethout et al., 2017). Specifically, Zoethout et al. (2017) used a coding scheme developed by Veldhuis-Diermanse (2002) to distinguish task-related interactions from nontask-related interactions. Zoethout and colleagues defined a task-related interactional sequences by noting when a task-related query or statement was followed up by another task-related query or statement, ending when there was (1) more than five seconds of silence or (2) nontask-related speech following task-related queries, per guidelines by Hogan et al. (1999). The study found that transactivity, or acting on each other's reasoning, affects team learning. In another example, researchers examined how team members' messages can be interpreted differently by different people (Beck & Keyton, 2009). Interaction process analysis (IPA; Bales, 1950) was used to analyze communication during team meetings. Beck and Keyton (2009) used a retrospective analysis technique to interview meeting attendees while watching a portion of the video-recorded meetings with the researchers. The participants explained their thought process behind their behavior and their perception of teammate behavior during the video-recorded interactions; their interviews were subsequently analyzed. Altogether, this study demonstrated how team members can interpret the same interaction differently. A more in-depth review of an interaction analysis study follows.

A study of team communication in meetings used the act4teams coding model to test the strength of correlations (1) between team communication and team outcomes and (2) between team communication and organizational outcomes (Kauffeld & Lehmann-Willenbrock, 2012). This study used the input-process-output (IPO; Mathieu et al., 2008) model and conceptualized the team processes as different components of the act4teams coding scheme to test the relationships between the processes and team and organizational outcomes (Kauffeld & Lehmann-Willenbrock, 2012). The act4teams coding scheme was created as a taxonomy for empirical team observations; it contains 44 observation categories (e.g., interrupting) divided into 12 interaction aspects (e.g., negative socioemotional statements) and four types of team interactions (i.e., problem-focused statements, procedural statements, socioemotional statements, and action-oriented statements; see Kauffeld & Meyers, 2009; see Lehmann-Willenbrock et al., 2011). In Kauffeld and Lehmann-Willenbrock's (2012) study, the researchers recruited 92 non-hierarchical teams in several industries (e.g., packaging, automotive supply) and videotaped a one-hour team meeting. Participants were instructed to ignore the camera. The videos were coded so each phrase was assigned only one code; a small portion of videos were double coded to calculate inter-rater reliability, which was at an appropriate level (Cohen's $\kappa = 0.90$). Each team interview was coded for the number of phrases in each of the 44 observation categories and 12 interaction aspects. These counts were correlated with meeting satisfaction ratings, team productivity ratings, and organization success ratings. The study found far-reaching effects of meeting behavior; for example, criticizing others in meetings had a strong, negative correlation with meeting satisfaction and organizational success.

Content Analysis

Traditionally, content analysis has been used to systematically codify large amounts of text (e.g., interviews, newspaper articles), reduce it into more manageable information, and make valid inferences about the message, the sender, or the receiver (Weber, 1990). Others broadly define content analysis as objectively and systematically identifying characteristics of messages and therefore include written, verbal, or visual communication in a variety of data forms (e.g., videotaped interactions; Cole, 1988). A common misperception is that content analysis simply implies conducting a word frequency count (Stemler, 2015); however, the collection of analytic techniques included in content analysis extends far beyond this. In fact, this methodology encompasses several strategies used to analyze text and other data forms and can be applied in a quantitative (e.g., frequency counts), qualitative (e.g., exemplar quotes), or mixed-methods capacity (Smith, 2015). Due to the methods' combination of qualitative and quantitative components, we consider content analysis to be an integrated mixed methodology. Specifically, content analysis creates a platform via qualitative inferences about the data for researchers to impose a quantitative lens, exemplifying our notion of an integrated mixed method. Five studies published in *Small Group Research* have used content analysis (Black et al., 2011; De Wever et al., 2008; Letendre & Davis, 2004; Müller et al., 2009; Strijbos et al., 2004).

Content analysis is a versatile method that allows the researchers to synthesize large amounts of data into manageable categories (Weber, 1990). It is a useful general analysis tool, especially for exploratory research. Like other mixed methodologies, there is not one right way to conduct content analysis, and different methods are appropriate based on the phenomena of interest and the research question. In content analysis the categories or concepts applied must be valid indicators of the construct the researcher intended to measure; likewise, the coding procedure must be reliable and consistent (Weber, 1990). Reliability issues typically stem from ambiguity in the defined categories, the coding rules, or the meaning of the words themselves. The development of explicit coding instructions and use of these instructions to train all coders is one way to overcome potential threats to reliability (Stemler, 2015). Validation strategies often include triangulating data from many sources, having participants review results and edit if necessary, and having other researchers review study procedures (Creswell, 2007). In addition, researchers using content analysis are often asked to report reliability statistics such as Krippendorff's alpha or Cohen's kappa; see Krippendorff (2004) for a review.

Benefits and drawbacks. Humphrey and Aime (2014) emphasize the need for multi-level, multi-period frameworks (including social relations modeling, longitudinal research, and round-robin designs); however, they also acknowledge the potentially burdensome amount of data collection required in these efforts. Content analysis may help tackle this issue by allowing for the inclusion of a wide range of data sources (e.g., text, visual, audio), including data sources that do not burden study participants (e.g., email or chat messages, archival records), and data sources that are traditionally underutilized (e.g., media content such as organizational websites or bulletins; Neuendorf, 2017; Stemler, 2015). A benefit of content analysis is that it enables researchers to sift through large amounts of data in an organized and replicable fashion, systematically coding and subsequently categorizing information (Grbich, 2007). Content analysis also allows for immediate feedback on the researcher's emerging questions, making it possible to move iteratively between analysis and theory development (Silverman, 2000). Content analysis may make detailed, emergent, longitudinal teams research and theory-building more accessible due to its usefulness for large data sets.

There are specific limitations associated with each approach to data analysis. For example, in content analysis synonyms may be used for stylistic reasons throughout the text and if not included in the category, synonyms could skew frequency counts (Stemler, 2015). This can be overcome by careful inclusion of synonyms in a master codebook. Alternatively, words may have multiple meanings, and could be erroneously included in a frequency count. In-context verification or use of a Key Word in Context search, which pulls surrounding data, can be used to overcome this potential pitfall. Relatedly, adherence to a strict codebook can result in training qualitative coders to narrowly interpret the data (Smith, 2015). Content analysis often includes an approach that is at least in part quantitative and involves significance testing, discouraging the analysis of the surrounding context or of unique communications or text that cannot be reduced (Krippendorff, 1980). The method also requires stable and unambiguous interpretations of data and can fail to capture the way specific meanings in communication can evolve over time. Finally, there is an inherent trade-off between generalizability and capturing the richness of the data between use of an inductive (coding categories derived from data) or deductive (coding categories are derived from existing theory) approach (Krippendorff, 1980).

Exemplars from the literature. Content analysis has been used alone and paired with other techniques to analyze data in teams and groups studies. For example, a study of television show production teams used a deductive content analysis, called pattern matching, of interviews with directors to test whether charismatic leadership theory applied to television directors (Murphy & Ensher, 2008). Murphy and Ensher (2008) used a software called DICTION[2] (Hart, 2000), which used over 31 dictionaries with over 10,000 search words to calculate the relative percentage of words spent on a construct. Another study used content analysis of interviews with 19 leaders to study shared mental models in self-managed work teams (Druskat & Wheeler, 2003). This research used an inductive approach paired with frequency counts for behaviors and reliability checks for the coding. Druskat and Wheeler (2003) built a multilevel boundary-spanning model that includes four functions (relating, scouting, persuading, and empowering) to support team effectiveness. Below, we present a more in-depth examination of the use of content analysis using an integrated methods approach.

Gibson and Gibbs (2006) aimed to unpack distinct dimensions of virtuality, consider the unique effect of each dimension on team innovation, and examine the moderating role of a psychologically safe communication climate. Gibson and Gibbs use content analysis to target conceptual and methodological limitations of previous studies, including discrepancies in number and complexity of virtuality dimensions across frameworks and the tendency to lump dimensions together without examining the differential effects.

Gibson and Gibbs (2006) began with an exploratory inquiry, conducting 177 interviews across 14 teams representing seven industries, 18 nations, and 16 organizations. Content analysis was first used to establish measures of psychologically safe communication climate and innovation based on individual interview data. Using a deductive approach, a list of key words pertaining to each concept was compiled based on previous survey instruments, research articles, and a snowball technique using synonyms found in dictionaries or thesauruses. They searched for words related to each concept, with in-context verification conducted by independent raters. Finally, a frequency count was computed for each individual interviewee for each concept; data were aggregated to the team level and used to explore the relationships between virtuality, climate, and innovation.

Gibson and Gibbs formally tested their hypotheses using a quantitative approach with survey data from 56 design teams. The empirical data offered additional support for the independent and differential effects of each dimension of virtuality on innovation, and the mitigating role of a psychologically safe communication climate. Content analysis was used to provide evidence that four characteristics of virtuality (i.e., geographic dispersion, electronic dependence, structural dynamism, and national diversity) are not highly related, and have independent, negative effects on innovation. These findings demonstrate how content analysis can benefit teams research by putting forth more nuanced constructs, which can be used to explore critical relationships in teams research that have persistent equivocal empirical support (e.g., diversity and communication; Stahl et al., 2010).

Cluster Analysis

Cluster analysis is a data reduction method that aids in the analysis of large data sets (Namey et al., 2008). This method is used to group together homogenous participants or groups within a sample and is especially useful for data mining or exploratory research with a multitude of variables (Salas et al., 2015). Cluster analysis can utilize both bottom-up or top-down approaches. In a bottom-up approach, the researcher carefully familiarizes themself with the raw data, or reads and rereads initial text, looking for keywords or themes in the data that will help inform the analysis (Namey et al., 2008). Then the researcher creates a similarity matrix to aggregate the similarities across all the included variables. Using this methodology, each observation starts as its own cluster, and clusters are merged as the researcher progresses up the hierarchy, with the three most common algorithms for clustering including single linkage, average linkage, and complete linkage (Guest & McLellan, 2003). Due to the researchers' involvement in choosing the variables to use in the analysis of participant or team similarity and the addition of statistical metrics, we consider cluster analysis an integrated mixed method. Only two studies published in *Small Group Research* have used cluster analysis (Driskell et al., 2017; Shaughnessy & Kivlighan, 1995).

The first step in preparing the coded data for cluster analysis is to generate a (binary or similarity) matrix (Guest & McLellan, 2003). This includes displaying observations in a descriptive matrix; for example, displaying numerical distance or likeness between data points. The second step is to graphically display the unit of analysis (e.g., code) by unit of observation (e.g., participant/respondent interview). Importantly, the graphic display can integrate prior analysis (e.g., frequency and salience tables). Codes grouped at higher levels can suggest high frequency or saliency within the qualitative text, and codes in the same cluster can signify codes that tended to co-occur together. Next, the researcher can move between the text data and cluster analysis to add quotes or details from the raw data. As applied to teams research, Namey et al. (2008) suggest using a combination of complementary data reduction techniques (e.g., combining with content analysis as an initial method of filtering). The researcher may also calculate statistical tests of distance (such as Euclidean distance) to quantify any differences between clusters (Finch, 2005).

Benefits and drawbacks. Cluster analysis incorporates components of the Delphi method, as it allows experts to arrive at a consensus on the categorization of data. This may be particularly useful when establishing a new construct and connecting it within the established literature. Hierarchical cluster analysis is often a bottom-up methodology, as all observations or codes start out separately at the first step, and associated codes in the data set are combined or merged as the analysis continues (Kaufman & Rousseeuw, 2009). The technique graphically depicts the relationships between observations (e.g., codes) and provides a broader, more holistic perspective (Namey et al., 2008). Hierarchical cluster analysis is designed to identify the structures of categories that fit a collection of observations, allowing the researcher to identify natural groupings, or the overall structure of codes.

As research on teams often includes multiple data collection efforts with individuals and teams over time, the potential for a significant amount of complex data is great. Cluster analysis can be used after initial analysis (e.g., structured coding, frequency counts, salience reports) of data to help interpret patterns in rich data sets with multiple potential themes (Guest & McLellan, 2003). As a form of semantic network analysis, cluster analysis can help untangle and shape complex relationships such as those involved in teamwork (Barnett & Danowski, 1992). Put another way, the technique helps focus on the big picture and allows the researcher to begin to tell the story (Namey et al., 2008). Further, cluster analysis is used to find homogeneity within groups, and therefore may be a particularly useful tool for studying sub-groups within teams, such as finding whether the strategic core shares traits of interest or identifying potential faultlines when comprising a team. Likewise, cluster analysis can be used to identify homogeneity between teams.

Cluster analysis presents data in clearly defined clusters, representing an easily interpretable visual tool (i.e., meaningful, easy to read; Guest & McLellan, 2003). Additionally, cluster analysis allows the researcher to gain distance from the data and corroborate findings with other analytical strategies (e.g., code frequencies and isolated pairs of co-occurrences) such that the bigger picture is not lost. Finally, cluster analysis is especially useful for large data sets, which are common when studying individuals or subgroups across several teams. A notable disadvantage of this technique is the potential for bias on the part of the researcher when creating the initial matrices that act as an input for cluster analysis. These decisions can be largely subjective; therefore consistency is vital.

Exemplars from the literature. Researchers have used cluster analysis to study team-related constructs. For example, medical teams must learn how to execute patient handoffs. To understand how handoffs are best taught, researchers gathered a group of four experts to conduct a group concept map and analyzed consensus of the data with a hierarchical cluster analysis (Hynes et al., 2015). The group concept mapping with experts started with idea generation, next idea pruning (i.e., removing identical ideas, removing ideas that are irrelevant), then idea sorting into groups, and finally rating ideas on two values (importance and difficulty to achieve; Hynes et al., 2015). Next, Hynes et al. (2015) put the expert groupings on a two-dimensional map, used a stress value test to determine the maps' fit with the expert-provided data, and used a hierarchical cluster analysis to determine the number of clusters appropriate for the data. The analysis suggested there should be between five and 16 clusters; Hynes and colleagues took the solutions back to the four experts for a final cluster rating task and determined that a 10-cluster solution was the best fit. In another example, cluster analysis was used to understand how affective reactions can explain differences in educator teams' learning behaviors (Watzek & Mulder, 2019). Watzek and Mulder (2019) used SPSS to run a hierarchical cluster analysis on the team learning behaviors, including knowledge sharing, team reflection, and boundary spanning. There were three clusters from this analysis, which were validated in Mplus with a latent class analysis, confirming the three cluster results. Lastly, Watzek and Mulder ran an analysis of variance at the cluster level to determine the relationship between team affective reactions and team affective traits with team learning behaviors. Ultimately, Watzek and Mulder found that the differences between clusters of team learning behaviors could be explained by differences in team affective reactions. A more in-depth exemplar of cluster analysis is below.

In another example, Gilson and Shalley (2004) used cluster analysis to explore what influences a team's engagement in creative processes; specifically, they examine factors related to task design features, attitudes toward team activities, and team characteristics and interactions. Gilson and Shalley argue that while creativity has long been studied as a critical outcome or attribute of team effectiveness, little has been done to better understand what drives teams to engage in the creative process. Based in part on research conducted by Torrance (1988), Gilson and Shalley define team creative processes as "members working together in such a manner that they link ideas from multiple sources, delve into unknown areas to find better or unique approaches to a problem, or seek out novel ways of performing a task" (p. 454). Importantly, members have a choice and must be motivated (behaviorally, cognitively, and emotionally) to engage in this process. Gilson and Shalley hypothesize that the job requires creativity and interdependence, shared goals, active participation in problem solving, a supportive climate, moderate organizational tenure, and high levels of socialization will predict frequency of engagement in the creative process.

Using interview and survey data from the strategic business unit (SBU) of a large multinational organization, cluster analysis was conducted to classify teams in relation to the theoretical construct of interest (i.e., engagement in creative processes) using Ward's hierarchical method to plot solutions. Gilson and Shalley (2004) use a mixed-methods approach resulting in a comprehensive interpretation not possible by quantitative analysis alone. Gilson and Shalley also called for future research on what leads to innovation, and research on the interplay between the creative processes and other important team attitudes and behaviors (e.g., trust, conflict management). The methods utilized in this example article allowed Gilson and Shalley to (1) support hypotheses with a smaller sample size, and (2) add rich, detailed commentary on quantitative findings.

State Space Grids

State space grids are a temporally defined method that allows for visualization and quantification of team states for a moment-to-moment basis by tracking how a system changes on two categorical variables (Meinecke et al., 2019). As there have been many calls to study temporal team dynamics (Mathieu et al., 2017), state space grids can be a particularly useful method of uncovering the dynamic changes that occur over time in team composition, structural features, and mediating mechanisms. To complete a state space grids analysis, researchers should choose two theoretically related constructs, specify the mutually exclusive and exhaustive categories for said constructs, and create an accompanying coding scheme. Data may come from in-person observations or from audio or video-recorded observations (Meinecke et al., 2019). State space grids require the researcher to code the data used for the analysis, a typically qualitative procedure, and combine it with statistical analysis, a quantitative procedure. State space grids are a particularly underutilized, integrated mixed method, as zero state space grid studies have been published in *Small Group Research.*

Building on dynamic systems theory, this method draws parallels to the physics of electrons, noting that of the multiple states available within the system, an individual or team can only be in one state at a given moment (Thelen & Smith, 1994). This is the *states* while the *space grids* are accompanying figures that have an X and Y axis for the two constructs and a corresponding number of spaces as the number of mutually exclusive categories within each construct (Hollenstein, 2012). For example, if the constructs of interest were team satisfaction and communication quality, then there may be three categories for high, moderate, and low-quality communication as well as categories for high, moderate, and low-quality team satisfaction. Within these state space grids, some of the spaces may be attractors while others may be repellors; these terms refer to states that receive more or less activity, respectively, and have no bearing on the inherent goodness or productiveness of that state. Attractors are states on the grid that receive a lot of traffic because they are frequently visited and harder to leave; in our chosen example, an attractor may be the space representative of moderate-quality communication and moderate team satisfaction. Our example hinges on an assumption of normal distributions for communication quality and for team satisfaction, which would indicate the most likely state is a moderate value for both variables.

Patterns of behavior and responses may contribute to the attractiveness, or *stickiness* of a state; for example, teammates that learn from one another may create a mutually beneficial relationship and become stuck on the same state (Murphy-Mills et al., 2011). Other contributors to a state's stickiness include (1) the basin of attraction, or the range of states that lead to an attractor, and (2) local relaxation time, or how quickly a system returns to an attractor (Lewis et al., 1999). In some cases the stickiness is so strong that a team may lose its flexibility, or get stuck, in very few states for an extended period (Pincus & Metten, 2010). In contrast, teams are rarely at repellor states; for instance, it would make sense for high satisfaction and low-quality communication to be a repellor state (Hollenstein, 2007). When teams move from state to state, they are in a phase transition (Meinecke et al., 2019). Once the data has been coded, researchers may analyze the data in many ways, such as analyzing differences in the number of state visits or attractor analyses (Hollenstein, 2007; Meinecke et al., 2019; Saghafian, 2018).

Benefits and drawbacks. State space grids are an excellent way to study temporal dynamics when using two categorical variables, or variables that can be categorized. State space grids are a generally flexible method, which is a major benefit but comes with a warning. Studies that plan to use state space grids should know what constructs they plan to use as the two categorical axes prior to collecting data, as the constructs must be collected at the same time intervals. State space grids can accommodate long or short intervals (e.g., years or minutes), but if the data for the two constructs are not collected at the same time, they may not be included in the analysis. State space grids allow for many types of analysis, including how much time was spent in a specific state, the number of times a state was returned to, and length of time to go from one state to another (Meinecke et al., 2019). The adaptability in state space grids analysis may fit many testing needs, but it also necessitates that analyses have strong theoretical rationale.

Drawbacks accompany, yet do not invalidate, the benefits to state space grids. Some exploratory analyses with state space grids may become overwhelming if there is not a clear understanding of which variables belong on the two axes, but once the variables have been identified, state space grids may be useful for exploring and identifying temporal phenomena for more in-depth subsequent research. Whatever the data source, it must be temporal so that the method can be used to identify how processes occur at an intricate level. Overall, this is not an analysis completed with leftover data, as it would be very difficult to apply post-data collection. In addition, state space grids are not appropriate analyses for variables that cannot be categorized or for research questions uninterested in temporality.

Exemplars from the literature. Research on state space grids is not common in teams research, but there have been interesting studies of interpersonal interactions using the method. One example examines coach-athlete interactions in youth sports comparing the less successful and more successful pairings, as defined by team rank and athlete personal development (Erickson et al., 2011). Erickson and colleagues observed two teams to determine which behaviors were common. Those behaviors were used to determine the variables on the axes of the state space grid (one axis of coach behaviors and one axis of athlete behaviors); six hours of observations were coded such that they observed the actions of the coach and the time-lagged reaction of the athlete. Erickson and colleagues used GridWare (Lamey et al., 2004) to search for patterns in the data and found that (1) the more successful team had less variability in the interactions between the coach and athletes and (2) the coach on the more successful team was more likely to pair technical correction and positive reinforcement. In another example, researchers examined infant behavior with hypothesis-driven and exploratory research questions, including identifying attractor states (Lewis et al., 1999). Separation and reunions between a mother and infant were video-recorded and coded for two variables, intensity of infant distress and angle of infant gaze relative to the mother (Lewis et al., 1999). Lewis and colleagues used these two variables as the axes for the state space grid; they supplemented this analysis with a content analysis. Below, we explore one exemplar of space state grids research in more detail.

As state space grids are still uncommon in teams research, we chose to highlight a recent dissertation that used this method to study the co-occurrence of team cognitive processes and collective affective when responding to a crisis (Saghafian, 2018). In this study, participants were MBA student teams in a crisis management simulation; they needed to address allegations that their organization had used fraudulent data. The simulations were video-recorded and coded on a moment-to-moment basis for (1) collective affect and (2) cognitive processes, both based on previously established coding schemes. Collective affect was coded when collectively displayed by the teammates (e.g., aroused-positive, aroused-neutral) or coded accordingly when teammates' affect varied. Team cognitive processes were coded as (1) explicit versus implicit and (2) action-processing versus situation-processing; for example, information requests were considered explicit situation processing.

Saghafian (2018) then used two analyses to test her research questions. First, she used lag sequential analysis to determine whether the two coded variables at each instance (team cognitive processes and collective affect) were significantly related to each other. Saghafian used the lag sequential analysis to find differences in the co-occurrence of team cognitive processes and collective affective states between higher and lower performing teams. Then, Saghafian used the GridWare software to plot the trajectory of change in the co-occurrence of cognitive processes and collective affect over the course of the crisis, such that cognitive processes and collective affect are on the X and Y axes, respectively (see Figure 1). Saghafian conducted a whole-grid analysis and an attractor analysis using GridWare. The whole-grid analyses of state space grids measure the entire grid, primarily through variability in the trajectories. Attractor analyses indicate the relative frequency of co-occurrences between categories of cognition and affect. Ultimately, the analyses indicated that higher performing teams were more likely to experience only one attractor (team cognitive process- collective affect co-occurrence) while lower performing teams had numerous, weaker attractors. That is, high performing teams establish a behavioral habit that reoccurs quickly and frequently over time. Specifically, high performing teams were more likely to experience speaking up, planning and instruction cognitive processes *plus* mid-arousal, neutral valence collective emotions. This dissertation laid the groundwork for understanding how crisis management teams can be cognitively and affectively effective.

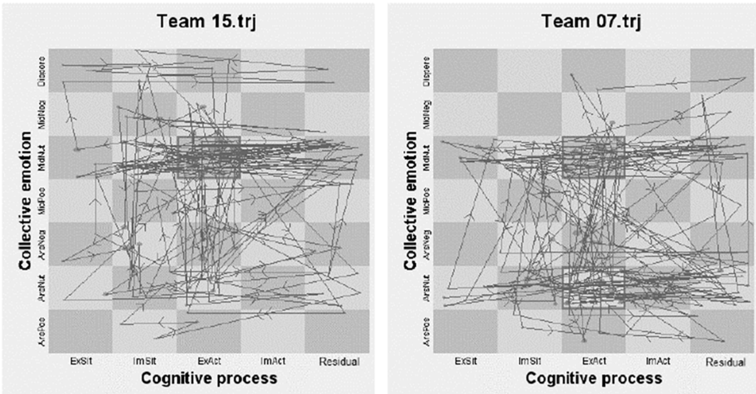


Figure 1. An example of state space grids comparing team emotion with team cognitive processes, from Saghafian (2018). Reprinted with permission from the author.

Agent-Based Modeling

Agent-based modeling is a form of computational modeling, which is an approach useful for studying complex systems with many moving parts. Broadly, teams researchers are interested in the dynamics of interacting individuals that operate as an adaptable collective. It is impossible to remove the complexities of studying multifaceted, dynamic interactions across multiple levels of analysis without sacrificing the essence of teamwork (see Mathieu et al., 2018). This reason alone is enough justification to consider agent-based modeling approaches. Agent-based modeling offers a way to study systems with emergent properties that result from interactions between agents, for which mathematical tools assuming static relationships are impractical (Axelrod, 1997). Although a comprehensive review spans beyond the scope of this paper, we provide here a brief overview and enough information to decide whether agent-based modeling may aid in a particular research effort. More in-depth information can be found in Tesfatsion and Judd's (2006) book and their accompanying web-based appendix.

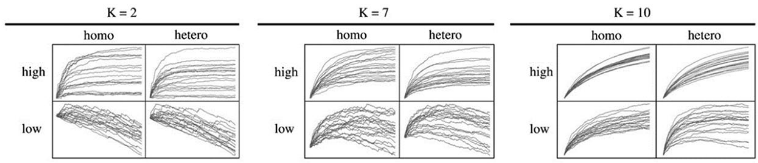
Agent-based modeling has been described as "a mindset more than a technology" (Bonabeau, 2002, p. 7280). Agent-based modeling uses controlled computational experiments and synthetic data to conduct research, a point of departure from the either inductive or deductive approaches typical in social science (Axelrod & Tesfatsion, 2006). It is widely applicable as an approach that can be used for making predictions about the results of parameter (or independent variable) changes through synthetic data generation (Bonabeau, 2002; Jackson et al., 2017; Malatesta et al., 2009; Zimmerman, 2007). For example, once an interaction is discovered, researchers can test the bounds of the interaction by changing the model's parameters. The most salient characteristic is that it does not involve the collection or analysis of original data, but rather, it generates data from built-in pre-specified assumptions based on qualitative and/or quantitative data and rules given to the agents to follow. Instead of evaluating a set of mathematical equations using collected data (e.g., in a structural-equation model), an agent-based model explores the operation of a system by considering all the functions of agents within the system and combinations of those functions. The goal of the model is to produce data that represents potential outcomes of a dynamic process. This is done by altering specific parameters of the model so that the researcher can develop a better and more complete understanding of the system as well as hypotheses testable with future data collection (Carley, 1999; Parunak et al., 1998).

As agent-based modeling relies on simulation rules, there is room to incorporate qualitative *and/or* quantitative data in the model to inform the simulation's states or rules for running (Tubaro & Casilli, 2010; Yang & Gilbert, 2008). The qualitative data can be sourced from interviews or observations (sometimes called ethnography), while the quantitative data can be derived from the literature or from previously unpublished research. Qualitative data must be quantified, often via a computer-aided qualitative analysis program, for use within an agent-based model (Yang & Gilbert, 2008). This data can inform program rules on how the agents (people or teams) meet, behave, receive outcomes such as rewards, and change over time (Jackson et al., 2017). Researchers should note that when using qualitative data in an agent-based model, the results are only generalizable to the contexts from which the data was collected (e.g., if the only observations used to inform a threshold rule were only collected from conducting observations within one hospital, then the results are only applicable to that hospital). Due to the potential of qualitative and quantitative components, Gilbert (2004) referred to agent-based modeling as a third approach, combining components of inductive qualitative and deductive quantitative research into computations representing team behavior. Agent-based modeling is an underutilized integrated mixed method, as there are zero *Small Group Research* studies using the method to date.

Benefits and drawbacks. Agent-based modeling involves the researcher setting the simulation rules, which can be derived from prior research; it is useful for a host of research questions, including studying emergence, multilevel effects, and adaptive behavior. A clear advantage of agent-based modeling is the ability to test statistical models without sacrificing realistic assumptions of non-linearity common to a complex system (Harrison et al., 2007). In addition, agent-based modeling is advantageous for scientists studying teams because it considers multiple levels of influence, including the agent's individual characteristics, such as age or gender, and group level effects such as team compositional change (Yang & Gilbert, 2008). Small details such as individual agent characteristics (i.e. memory; Bonabeau, 2002) can be modeled alongside structural and group data (e.g., who talks to whom and when; Yang & Gilbert, 2008) through member interactions. Agent-based modeling is considered especially useful for studying (1) emergent behaviors, (2) interactions between agents that are nonlinear or discontinuous, (3) heterogeneous populations, and (4) agents that display learning or other forms of adaptive behavior (Achorn, 2004). Perhaps this is why there have been calls to study team leadership with agent-based modeling (Carter et al., 2015).

One of the greatest hurdles a researcher may encounter with agent-based modeling is the stark difference from our traditional statistics-based research arsenals. The tools of agent-based modeling stem from computer science, and opportunities to cross-pollinate between teams researchers and computer science domains are rather rare. This means teams researchers may need to seek out collaborations with those well-versed in computer science and systems engineering who are familiar with the different types of software programs that can be used to run simulations. Researchers should be considerate as to where they derive the data that informs simulation rules. If the desired outcome is for a very specific context, then the data inputted into the simulation should be close to the context (e.g., to predict a surgical team's success, use data from surgical teams), but if a more general outcome is desired then the researcher should use more generalized data such as meta-analytic findings.

Exemplars from the literature. Research on teams and groups has relied on agent-based modeling alone and in conjunction with other methods. In one study, researchers compared leadership emergence in virtual teams with face-to-face teams with agent-based modeling and then with experimental tests (Serban et al., 2015). Serban et al. used literature reviews to determine the parameter values used in the model (for characteristics like cognitive ability, personality, self-efficacy, and comfort with technology) and rules for interactions. They inputted this information into the model using the Python programming language. In another study, researchers used agent-based modeling with an experimental design to examine situational awareness management in teams (Kitchin & Baber, 2016). First, Kitchin and Baber (2016) used an experiment to determine the effects of similar views versus different views for each team member on a situational awareness task. They used an



Note: Each of the graphs above shows 20 time series plots, which correspond to 20 independent simulation results in each parameter setting. The horizontal axis indicates time while the vertical axis indicates development of mental models (i.e., change of their convergence level relative to initial values). The labels "homo" and "hetero" correspond to homogenous groups (H=0) and heterogeneous groups (H=1), respectively, while the labels "high" and "low" correspond to high levels of mutual interest (M=1) and low levels of mutual interest (M=0), respectively. K=2 reflects the in-group is the minority (LMX); K=7 reflects the in-group is the *majority (LMX); K*=10 represents participative leadership.

Figure 2. Agent-based models of three types of teams differing on density (left to right is low to high density). The convergence of the teams' mental models is illustrated here, from Dionne et al. (2010). Reprinted with permission from Elsevier.

agent-based model on NetLogo to replicate the experiment with modified expertise of agents, or teammates, and ran the model 100 times, for a sample size of 300 teams. The results indicate that expertise, situational awareness, and team performance are related. We discuss one exemplar of agent-based modeling in-depth below.

Dionne et al. (2010) used agent-based modeling to investigate the phenomenon in teams where individual information processing begins to converge and shift to collective processing, a process known as shared mental model convergence. Prior to this research, little was known about how leadership might facilitate this dynamic process. Dionne et al. (2010) created an agent-based model using an established framework where teams first orient themselves, then differentiate their knowledge, and lastly integrate to develop a shared mental model (see Macomb, 2007). They hypothesized that leadership and team properties have the potential to impact mental model convergence in different ways at each stage of this process (Dionne et al., 2010). Ultimately, findings from the simulation demonstrated how participative leadership may facilitate mental model convergence and problem-solving performance when team members have diverse domain expertise, but performance tended to suffer when teams with similar expertise had participative leadership structures (see Figure 2).

Using agent-based modeling, Dionne et al. (2010) were able to simulate (1) whether team members share expertise, (2) how they responded to each other's input, and (3) how input was integrated into their understandings. Their findings are indeed complex and would be difficult to observe and measure in real teams, as finding a large enough sample size for each condition would be unfeasible. Moreover, assessing cognition-based constructs, such as shared mental models, can be challenging for teams researchers. Simulations do not require assessment tools, but simply theory-based assumptions of potential outcomes. Overall, although this work was exploratory in nature, it allowed the researchers to answer the what-ifs of leadership's impact on mental model convergence to illuminate potential areas for future work.

Discussion

The central goal of the present review is to make a case for more integrated mixed methods research and demonstrate how it may benefit teams research through exemplar methods underutilized in teams research. Specifically, we have described five integrated mixed methods, the benefits and drawbacks for applying each method, and exemplars of each in teams research. We emphasize that the integrated mixed methods here are not replacements for other methods available in our field. However, we posit that integrated mixed methods may be more enlightening than triangulated methods when studying particularly complex issues embedded within team dynamics, as qualitative and quantitative components of integrated mixed methods serve to build off each other rather than confirm findings. Therefore, we offer this review of methods as a resource to teams researchers in hopes it will facilitate the increased and appropriate use of integrated mixed methods to investigate such issues.

Practical Implications

We intend for this review to help teams researchers incorporate previously underused methods into their methodological repertoires. The methods discussed in this paper vary in their purpose and the research phenomena they best address, and a careful process to choose the most appropriate method should be followed. The first step in the decision process involves understanding the research question at hand and the scope of the study, including identifying the purpose and expected results (Schoonenboom, 2018). This information should be used to narrow down the methods that may be helpful for the stated research aims. Table 1 may help researchers in choosing a method. When choosing a method appropriate for the research aims, the techniques discussed in this paper can be used with both group and individual level data. The data type and study context for the examples and exemplars from this review are listed in Table 2.

Overall benefits and drawbacks for integrated mixed methods. Teams research using integrated mixed methods should enrich the field by combining the

Table 1. Summary of Analyses.

Method type	Why it is an integrated mixed method	Type of teams research question answered	Type of data used	Where to learn the method
Interaction analysis: an approach to understanding communication, derived from ethnography and conversation analysis	Relies on participants' experiences, self-described cognition, and statistical results	(1) Temporal (2) Cognition (3) Dyadic and sub-group analyses	Observations	Bales (1950), Beck and Keyton (2009), Grossen (2010), and Jordan and Henderson (1995)
Content analysis: data reduction method that aids in the analysis of large data sets	Relies on participants' experiences and statistical results	(1) Exploratory (2) General team dynamics	(1) Interview (2) Surveys (3) Archival data	Krippendorff (1980), Neuendorf (2017), Stemler (2015), and Weber (1990)
Cluster analysis: objectively and systematically identifying characteristics of messages and communication	Relies on participants' experiences and statistical results	(1) Exploratory (2) General team dynamics (3) Dyadic and sub-group analyses	(1) Surveys (2) Archival data	Guest & McLellan (2003), Kaufman & Rousseeuw (2009), and Namey et al. (2008)
State space grids: temporally defined method that tracks how a system changes on two categorical variables	Researcher-coded data + statistics	Temporal	Observations	Hollenstein (2013), Lewis et al. (1999), Meinecke et al. (2019), Pincus and Metten (2010), and Thelen and Smith (1994)
Agent-based modeling: a form of computational modeling, which useful for studying complex systems with moving parts	Researcher involvement in setting simulation parameters	(1) Emergence (2) Dyadic and sub-group analyses	Findings from the literature or past research	Axelrod and Tesfatsion (2006), Bonabeau (2002), Jackson et al. (2017), and Yang and Gilbert (2008)

Table 2. Analyses Exemplars.

Exemplars	Data type	Study context	Used with another method?
Interaction analysis			
Zoethout et al. (2017)	Group	Educator teams	–
Beck and Keyton (2009)	Individual	Internet service provider leader-member dyads	Retrospective analysis
Kauffeld and Lehmann-Willenbrock (2012)	Group	Non-hierarchical industry (e.g., metal) team meetings	–
Content analysis			
Murphy and Ensher (2008)	Individual	Television show directors	–
Druskat and Wheeler (2003)	Individual	Self-managed work teams	Cluster analysis
Gibson and Gibbs (2006)	Individual	Work teams from 7 various industries (e.g., aerospace, agriculture, retail)	–
Cluster analysis			
Hynes et al. (2015)	Individual	Medical teams	–
Watzek and Mulder (2019)	Group	Interdisciplinary vocational educator teams	–
Gilson and Shalley (2004)	Individual	Self-managed work teams	No, but an ANOVA was used to test the cluster classification and Tukey comparisons were used to differentiate the clusters
State space grids			
Erickson et al. (2011)	Group, dyadic	Coach-youth athlete interaction	–
Lewis et al. (1999)	Individual	Mother-infant dyad	–
Saghafian (2018)	Group	MBA student teams	Lag sequential analysis; log-linear analysis; whole-grid analysis and attractor analysis
Agent-based modeling			
Serban et al. (2015)	Group	Interdisciplinary student project teams	Other forms of computational modeling
Kitchin and Baber (2016)	Group	Ad hoc student teams	–
Dionne et al. (2010)	Group	Problem-solving work teams	–

benefits of qualitative research with quantitative research in one analysis. Qualitative research maintains a human-centric view, while quantitative findings are applicable across many contexts. Integrated mixed methods synthesize the benefits into one study. Thus, the qualitative and quantitative components build off each other in an integrated mixed methods study. In the present paper, we cover five such methods, but more methods exist in the literature that may fit with our conceptualization of integrated mixed methods, such as social network analysis, which includes researcher-coded data and statistical analyses (e.g., D'Angelo & Ryan, 2016). In all, these methods stand to especially benefit context that are otherwise difficult to study using traditional research methods, such as small teams and high-reliability teams that operate in especially dangerous contexts, as well as uncover novel team phenomena.

Integrated mixed methods can be useful in tackling many of the challenges inherent to studying teams, challenges that more traditional methods are often incapable of fully addressing. First, integrated mixed methods allow for a wider range of data sources than are typically used in teams research (e.g., visual and audio data, email, organizational websites, media content). These alternate forms of data require different tools to analyze and can otherwise be too burdensome for researchers. Many of these methods also aid in the reduction of large data sets, which may support exploratory research and identification of new constructs for phenomena that are not yet fully understood. Integrated mixed methods can also display data in new and unique ways, allowing otherwise difficult to discern patterns in data to emerge. As sample size is a pervasive problem in teams research, integrated mixed methods can also allow analyses of smaller sample sizes or of computer-generated data. Additionally, integrated mixed methods can aid in longitudinal research and identifying distal outcomes of teamwork (e.g., organizational success). They can provide rich, moment-to-moment data on the state of a team, useful for uncovering dynamic changes in the input, processes, and contextual variables that affect team performance over time. Put another way, these methods may more readily capture the temporal, complex, multi-level, and dynamic nature of teamwork.

The benefits to be gained through integrated mixed methods are several, but these methods are not without their challenges, as there are drawbacks with any method. The adoption of many of the methods we describe necessitates a great deal of work upfront to ensure researchers have a clear plan before data is collected. This challenge is not particular to integrated mixed methods, but the upfront work required for these methods might be considered cumbersome compared to more commonly used conventional methods. For instance, for teams researchers who may have less expertise using mixed methods, developing a successful project may require interdisciplinary collaborations with those in other domains who are more expert at using these methods. Moreover, some investment in training will be needed before using a new method. With this paper, we hope to have facilitated this process and contribute a resource with enough information to get researchers started in the right direction. Overall, the potential drawbacks of using integrated mixed methods are worth overcoming for richer, more dynamic, and temporally focused teams research.

How to implement new methods. We recognize that implementing new methods is challenging, both technically and socially. The technical challenge comes from learning the new methods, either through others or self-taught. However, resources such as libraries and online tutorials may make this task less daunting. On campuses, many libraries, data resource centers, and lecture series can provide information on specific methodologies. Additionally, a simple internet search of a method may lead to tutorials of interest. If a specific program is used for the method (e.g., R or ATLAS.ti), there are often resources such as step-by-step instructional guides available on the websites attached to the platform. Then, the social challenge comes from seeking to publish with a method that is unconventional in one's field. For researchers considering methods in this review, frustrations may lie in proving the methods' fit for the research topic and defending use of a previously uncommon approach. This may also pose a stumbling block for editors, who must identify qualified reviewers. Therefore, we recommend researchers cite methods papers from related disciplines paired with a substantial explanation of the method and why it is a reasonable fit for the study at hand. Likewise, submitting to a journal that specializes in interdisciplinary research may be valuable, as researchers can expect editors and reviewers to have more diverse backgrounds, which may lead to greater acceptance of a method. Although finding an expert in one's own field may prove difficult, reaching across academic disciplines for mentoring is another useful approach.

Conclusion

In this article, we highlighted underutilized methods that are strategically advantageous and uniquely suited to study team-level phenomena. Researchers are often faced with a dilemma of choosing highly involved, less common qualitative methods, or quantitative methods that may not completely capture the full characterization of dynamic emergent states and team processes. By highlighting five integrated mixed methods we demonstrate solutions for systematically capturing ongoing and retrospective processes, as well as emergent states without losing the ever-important context of the workplace.

Teams are becoming more complex as the nature of work is changing. These added complexities may be more obvious in some parts of the teams literature, such as multiteam systems and virtual teams, but added complexity is more common throughout the modern workplace as work becomes less stable, more automated, and globalized (Blustein, 2013). The notion of requisite complexity suggests that a system should possess sufficient complexity to be effective within its environment; similarly, our methods should be sufficient to assess complex teams (Boisot & McKelvey, 2011). Integrated mixed methods allow us to continue studying teams in the wild because they capture the richness of the context in which teams operate while providing reproducible findings that encompass what teams experience, how their experiences translate to performance, and how to predict their performance. Our highlighted methods are not the only options, but they may assist in illuminating a path forward for team-level research that addresses their complex nature.

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Notes

1. Throughout this paper, and reflecting much of the existing literature, we use the terms “group” and “team” interchangeably.
2. Please note that DICTION does not analyze phrases or sentences, only individual words.

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