Applying Systems Science to Advance Research on Team Phenomena

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Abstract

The recognition of teams as complex dynamic systems was a hallmark and among the earliest considerations of research on team functioning. However, the popularization of conceptual heuristics such as the input-process-outcome (IPO) framework and the accessibility of methodological, analytical, and meta-theoretical principles from multilevel theory (MLT) have resulted in a disconnect between contemporary theory and empirical research on teams and this foundational perspective. Thus, the primary motivation for the present paper is to facilitate and stimulate future research on team phenomena that embraces systems thinking. To do so, we describe key concepts, terminology, and ideas from specific branches of the systems sciences—namely open systems theory, dynamical systems, and agent-based systems—that have direct relevance for researching team phenomena as complex systems. Additionally, a comparison between two example models of team performance that are rooted in an IPO+MLT versus a systems-oriented perspective is offered to highlight the difference in foci, applications, and inferences these approaches offer. The paper concludes with a summary of key advantages as well as potential obstacles for reintroducing systems-thinking back into team science.

As the nature of work has continued progressing towards more complex tasks and operational environments, teams have increasingly become the primary unit of work for organizations (Bersin et al., 2017; Mathieu et al., 2019). Teams are also relied upon to carry out many of society's most vital functions, such as performing medical procedures, conducting humanitarian operations, and advancing scientific breakthroughs (Kozlowksi & Ilgen, 2006). Understanding how to support, maintain, and facilitate high performing teams thus represents an area of critical importance. In recognition of this significance, the past 40 years of organizational science has witnessed an exponential increase in the amount of published research on work team functioning (Mathieu et al., 2017).

In taking stock of the progress that has been made in our understanding of teams and team performance over this time span, it is informative to consider how the organizational sciences have tended to conceptualize teams and their functioning. For example, several taxonomies for classifying team properties have been proposed, such as characteristics of groups versus teams (e.g., membership, boundary permeability, entitativity; Forsysth, 2019), the types of actions teams engage in to facilitate taskwork (e.g., transition, action, and interpersonal processes, Marks et al., 2001), and differences in the context and nature of work performed by teams (e.g., action teams, decision-making teams; McGrath, 1984; Sundstrom et al., 1990). Beyond these classification schemes though, one of the earliest and foundational characterizations of teams is the recognition that they operate as *complex dynamic systems* (Allport, 1924; Lewin, 1943; Parsons, 1937; Sherif et al., 1955). That is, teams are collections of unique yet interdependent individuals who engage in behaviors and interactions with one another and a commonly experienced environment to satisfy personal goals and collectively recognized demands. Through these exchanges, unique social structures (e.g., norms, roles, cultures), affective and cognitive perceptions (e.g., trust, knowledge, cohesion), and patterns of behavior can manifest that both describe and shape how teams and their members function and perform (Arrow et al., 2000; Cronin et al., 2011; Katz & Kahn, 1978; Kozlowski & Klein, 2000; McGrath, 1991; Weick, 1979).

Given the historical precedent and widely acknowledged view of teams as complex systems, it is surprising that so little conceptual and empirical work has accumulated on teams in the social and organizational sciences that corresponds with this foundational perspective. A recurrent theme in contemporary reviews of the literature is that the modal theories, methods, and empirics directed towards teams treats them as static, holistic, and often anthropomorphized entities (e.g., teams "possess" personality, cognitive ability, trust, etc.; Crawford & LePine, 2013; Cronin et al., 2011; Kozlowski et al., 2013; Humphrey & Aime, 2014; Mathieu et al., 2019; Waller et al., 2016). In other words, teams have most commonly been described in ways that reify them as aggregated, homogenized, and undifferentiated "wholes" rather than rich, interactive, and dynamic systems.

A consequence of viewing "teams as wholes" versus "teams as systems" is that the former tends to promote theory, measurement, and analytic techniques that focus almost exclusively on the extent to which attributes, perceptions, behaviors, etc. are consensually shared among team members and the extent to which that shared content correlates with other similarly formulated team-level variables at the population level (e.g., teams with higher shared perceptions of team cohesion exhibit stronger correlations with team performance on average; Klein et al., 1994; Dansereau et al., 1999; Kozlowski et al., 2013). Besides failing to capture the inherent dynamics of the team system, this focus generally neglects examinations of *how*, *why*, and *what teams do* to function effectively that could provide actionable guidance for facilitating team performance (McGrath & Tschan, 2007). We do not wish to imply that the past four decades of research on teams has been unfruitful or unproductive. On the contrary, the field has identified many useful constructs and accumulated valuable knowledge about teams, and we suspect that team science will continue to observe incremental improvements in understanding under the current paradigm (e.g., Mathieu et al., 2017; Waller et al., 2016). However, we posit that there is considerable potential for advancing team science by more purposefully incorporating and embracing teams as complex systems.

The primary goal of this paper is thus to provide a primer on systems thinking for the teams researcher and its utility for advancing theory and research. We first describe several key concepts and terminology from the broader domain of systems science and their relevance for representing team phenomena. Next, we highlight critical differences in the foci, applications, and inferences that can be advanced from adopting a systems approach to team functioning relative to those afforded by contemporary approaches by contrasting two example models of team performance from both perspectives. We then conclude with a summary of the strengths and likely challenges of incorporating the systems-based approach for conceptualizing and researching team phenomena.

Current Paradigm for Studying Teams in the Organizational Sciences

Before elaborating on a systems-oriented perspective to teams research, it is useful to describe the prevailing paradigm for studying teams in the social and organizational sciences. Contemporary theory and research have arguably been shaped most significantly by two seminal perspectives: (1) the input-process-outcome (IPO) framework of team functioning (McGrath, 1964) and its derivatives (e.g., the Input-Mediator-Outcome-Input (IMOI) framework; e.g., Ilgen et al., 2005; Mathieu et al., 2008) and (2) the “meta-theoretical” principles of multilevel theory (MLT; e.g., Kozlowski & Klein, 2000).

The IPO framework has provided a useful and widely adopted heuristic for discussing factors related to team effectiveness. *Inputs* in the IPO framework refer to the attributes of members (e.g., knowledge, skills, abilities, dispositions), the team (e.g., norms, roles), and the organization/environment (e.g., resources, time demands) that constitute a team’s operational conditions. *Processes* are generally described as the actions of team members that facilitate task accomplishment and produce characteristic patterns of social interaction and structure (e.g., trust, climates, cohesion). Lastly, *outcomes* are the cumulative results of teams’ efforts and most commonly refer to performance-related outputs and affective/perceptual reactions (e.g., satisfaction, commitment). Although the IPO framework was never intended to reflect a theory or model of team functioning (McGrath, 1984), the causal chain it implies—in which a team’s inputs impact its processes which impact its outcomes—has shaped how researchers have described, studied, analyzed, and drawn inferences about teams for over half a century.

In contrast to the IPO framework’s specific focus on team functioning, MLT represents a broad collection of philosophies and methodological recommendations for considering phenomena involving collective entities (e.g., teams, multi-team systems, organizations). A fundamental tenet of MLT is that an organizational system can be characterized as a hierarchy of nested levels in which lower-level units (e.g., individuals) reside within higher-level units (e.g., teams). Two important consequents of this premise have strongly impacted the study of teams in the organizational sciences. First, substantively meaningful constructs can be conceptualized and operationalized at different levels of analysis (i.e., commitment represented as either/both an individual-level construct and a team-level construct). This proposition has inspired multiple decades of work devoted to developing conceptual frameworks, definitions, measurement approaches, and statistical indicators that capture constructs at different levels of analysis (e.g., Chan, 1998; Krasikova & LeBreton, 2019). Second, constructs residing at different levels of analysis can influence each other. This proposition has encouraged the development of elaborate conceptual models spanning multiple organizational levels and which attempt to capture how factors at the same and different levels of analysis relate to one another (e.g., individual-level attitudes and team-level cohesion simultaneously influence individual-level commitment). Efforts to test predictions from these conceptual models have also spurred the development of improved statistical models suitable for handling nested data structures (e.g., random coefficient modeling, Gonzalez-Roma & Hernandez, 2017; multilevel structural equations modeling, Preacher et al., 2010). In short, MLT provided organizational scientists with a valuable paradigm and readily understood standards for presenting theory, designing research, and analyzing data relevant to teams and their functioning.

In conjunction, the IPO framework and principles derived from MLT have engendered an approach to describing and modeling teams in a manner consistent with what Macy and Willer (2002) describe as “factor thinking.” In factor thinking, efforts to explain and develop an understanding of team phenomena are pursued through the identification of *consistent covariation* between two (or more) variables (Bechtel & Richardson, 1993; Smith & Conrey, 2007). Thus, a factor-thinking researcher who seeks to understand team performance would pursue this goal by identifying potential predictor variables (i.e., inputs such as team cognitive ability or team cohesion, or processes such as communication or coordination), employing approaches for quantifying those variables at the team-level (e.g., using statistical indices to determine whether members’ ability scores and ratings of cohesion can be aggregated, creating a score for a team's overall communication quality), and then examining whether those sets of factors reliably and regularly covary with team performance. Both the IPO framework—with its emphasis on classifying variables relevant to team functioning as inputs, processes, or outcomes and establishing the intervening mediating chain—and MLT—with its emphasis on defining aggregate constructs and exploring within- and cross-level relationships—readily equip the factor-thinking teams researcher with an accessible and potent toolkit for developing conceptual models and conducting empirical research.

Although factor thinking affords several strengths for describing and studying teams, an "actor thinking" approach represents an alternative perspective less commonly embraced by the organizational sciences but which is well suited for representing teams as complex systems (Macy & Willer, 2002). In actor thinking, efforts to explain and develop understanding of phenomena are pursued through the identification of *generative mechanisms* that characterize how one (or more) ongoing processes unfold and lead to recognizable patterns (Bechtel & Richardson, 1993; Smith & Conrey, 2007). Thus, an actor-thinking researcher who seeks to understand team performance might pursue this goal by examining how, when, and why individual members in a team engage in different activities (e.g., individuals possess multiple goals which they seek to accomplish), influence one another (e.g., task demands and individuals' unique goal pursuits create opportunities for interaction over time), and form relationships that lead to specific patterns/outcomes relevant to team performance (e.g., team members self-organize into smaller interconnected subgroups to accomplish taskwork). Through explicating and exploring these mechanisms and how they play out over time, the actor-thinking researcher seeks to describe how team performance emerges from the things that members *do* and how changes to those processes influence team outcomes, experiences, and trajectories under specific circumstances (Kozlowski et al., 2013). Actor thinking is thus directly aligned with the thesis of teams as complex dynamic systems in which collective phenomena (i.e., team performance, cohesion, conflict, trust, etc.) are conceived as continually unfolding consequences of the interactions within and between elements of a system (i.e., individuals and their actions).

We submit that factor thinking is the de facto and modal paradigm through which teams are considered in the contemporary organizational sciences. This perspective has been bolstered by decades of conceptual, methodological, and statistical work that have ingrained factor thinking into the cultural milieu of teams research. To reiterate, factor thinking can and does play a valuable role in summarizing basic predictions and aggregate descriptions of teams and their performance; it need not be completely abandoned. However, we believe that advancing the state of team science on topics such as team performance will require efforts to embrace and explicitly study teams in a manner more consistent with actor thinking. One of the challenges in shifting the teams research paradigm from factor to actor thinking is that many of the concepts, methods, and techniques of the latter are unfamiliar and rooted in the diffuse and disjointed domain of systems science (e.g., Epstein, 1999; Gorman et al., 2017; von Bertalanffy, 1972). In the following sections, we thus direct attention to key concepts from these areas that we believe are valuable for teams researchers interested in adopting a more actor- and systems-oriented view of team functioning.

Systems Concepts for the Team Scientist

A *system* can most generally be described as a collection of independent yet interconnected and interacting *elements* (von Bertalanffy, 1972). Like teams, systems are defined with respect to their boundaries that may vary across space (e.g., physical location of members, location of team members in a workflow network), time (e.g., changes in membership or responsibilities), and purpose (e.g., shifts in team and member goals). Systems are also commonly characterized as being embedded within an *environment* whose conditions (e.g., resources, task demands, policies) can influence and be influenced by the actions/outputs of the system and its elements. Given the breadth of applications and the interdisciplinary nature of systems science in general, several different philosophies, models, and methodological conventions exist for discussing and studying systems (social or otherwise). Although these varying perspectives share the common goal of characterizing systems as defined above, they often draw attention to and emphasize different aspects of system functioning in their interpretations and explanations. For purposes of the present discussion, we limit our focus to three branches of systems that are particularly relevant for advancing more systems-oriented treatments of team phenomena—open systems, dynamical systems, and agent-based systems.

Open Systems

The consideration of teams and organizations as *open systems* is among the earliest and most widely recognized systems perspectives in the social and organizational sciences (e.g., Katz & Kahn, 1978; Kozlowski & Klein, 2000; Parsons, 1937; Mathieu et al., 2008; von Bertalanffy, 1972). An open system is one in which material and energy can enter and leave through exchanges between the system and its environment (von Bertalanffy, 1950). For example, teams use their available equipment, information, and the capabilities of members (i.e., materials) to make products, services, and decisions that are subsequently distributed both within and outside the team to secure new resources. Further, teams transform these materials by continually drawing from and maintaining the affective/motivational, cognitive, and behavioral efforts of members (i.e., energy). Open systems are commonly contrasted against *closed systems* in which there is no net change in material or energy with the surrounding environment. By way of metaphor, an insulated and vacuum-sealed water bottle is a closed system as it is designed to keep its contents at the same level and temperature by preventing energy (e.g., heat) and material (e.g., water) from escaping or entering. In contrast, a cup with no lid is an open system as it is completely exposed to the environment and its contents can be influenced by the surroundings (e.g., water molecules can evaporate into the air, new substances can fall into the cup, heat is exchanged between the cup's contents and the surrounding air/surfaces). In this sense, a closed system is construed as completely isolated from its environment, whereas an open system is separate from yet in constant exchange with its environment.

In nature—and social systems in particular—there are few perfectly closed systems. Consequently, the significance of recognizing and treating teams as open systems is important for at least two reasons. First, the open systems view of teams emphasizes the critical importance of integrating a team's environment into explanatory accounts. There are numerous facets and ways in which a team's environment can be conceptualized (e.g., Ostroff, 2019, Meyer et al., 2019), including the physical environment, the task environment, and the sociocultural environment. Each of these embedding contexts reflects unique environmental facets with which teams and their members exchange material and energy. Environments also contain resources and demands that can facilitate or constrain (respectively) team functioning by placing differential value on certain member attributes, actions, and their distribution within a team (Guzzo & Shea, 1992; Mathieu et al., 2008). For example, the presence of stormy weather versus clear skies affects the criticality of attention, alertness, and communication among members in an air traffic control team to effectively carrying out it tasks.

Second, an implied condition of all open systems is that they are in "perpetual motion;" that is, they engage in near continuous exchanges of material and energy with their environment.

Notably, this is true even in situations where an open system is said to be “at rest” or equilibrium. Consider again the example of the sealed bottle versus the open cup. It is possible for both systems to achieve an equilibrium temperature wherein the heat of their contents does not change. However, the way in which these equilibria are reached and how they react to subsequent exchanges differs. In the closed system of the sealed bottle, an equilibrium temperature is attained once the heat contained in the air and liquid molecules trapped in the container has been equally distributed. Furthermore, this temperature will remain constant once reached unless new material/energy is added or removed from this system, at which point a qualitatively new equilibrium point should emerge (e.g., adding hot water to the bottle will raise the internal temperature of the contents to a new stable level). In contrast, the constant exchange between the open cup and its surrounding environment means that one would need to near *continuously* heat the contents of the cup to maintain its temperature at a given level. An open system can only maintain an equilibrium by continuing to import new material or energy from the environment. One can thus think of teams and their members as needing to continually generate effort—which necessitates a steady supply of support in the form of materials (equipment, information, etc.) and energy (motivational sources, capabilities, etc.)—to maintain a steady level of functioning (Katz & Kanh, 1978; von Bertalanffy, 1972).

An open system that has achieved this degree of homeostasis (i.e., rate of material/energy entering equals the rate at which material/energy is leaving) is said to be in a *stable or steady state* (von Bertalanffy, 1950). An important takeaway from the recognition of steady states in an open system is that, unlike in closed systems, it can be difficult to infer whether changes to the material/energy of an open system produce a demonstrable change if only the system’s outcomes are observed. For example, adding heat to the open cup may not raise the internal temperature of its contents if the rate at which heat dissipates from the cup also simultaneously increases. However, such changes should be evident in *how* the system is operating over time. Extending this insight to teams, changing the resources, capabilities, efforts, composition, etc. of a team may or may not influence its observable performance if the interactions, roles, behaviors, exchanges, etc. carried out by members adapt accordingly. Such *equifinality* (i.e., potential for any single state/outcome in a system to be achieved through different initial conditions and different processes) is common in open systems and yet another reason why focusing on how and what teams do (i.e., actor thinking) is critical for understanding team phenomena.

Dynamical Systems

In many respects, dynamical systems theory attempts to provide an overarching methodology, set of tools, and analytical frameworks for representing the behavior of open systems theory (cf., Thelen & Smith, 1994). Although some in the organizational sciences have equated the application of dynamical systems theory to teams with analyzing the trajectory of team-level constructs over time (e.g., autoregressive/dual change score models of team cohesion; Cronin et al., 2011; Matusik et al., 2019), the foundations of dynamical systems theory are broader and encompass efforts to capture *global* system features/patterns and their implications for understanding *local* occurrences. In the context of dynamical systems theory, local and global refer to whether the primary explanatory lens for a phenomenon is oriented towards a system's elements or the system itself, respectively (Gorman et al., 2017). For example, a local account for team cognition might focus on the extent to which similarity and overlap among the content of individual members' knowledge exists and the individual-level processes involved in producing convergence of those outcomes (e.g., how individuals' attention, memory, and information interpretation processes operate; Grand et al., 2016; Dionne et al., 2010). In contrast, a global account of team cognition might focus on identifying sequences of behavior that occur while teams interact and the extent to which those sequences represent generalizable, stable, and predictable patterns indicative of how teams learn (e.g., identifying and categorizing sequences of communication as indicative of different team learning functions; Cooke et al., 2013; Gorman, et al., 2009; Kennedy & McComb, 2014). This latter example is consistent with the dynamical systems approach to understanding team behavior as it seeks to describe and quantify a more "macro" system-level pattern of behavior rather than elaborate the more "micro" actions/processes carried out by specific individuals within that system.

A common technique for representing and summarizing the sorts of change dynamics represented in the dynamical systems perspective is through feedback loops (or multiple interlocking feedback loops). A *feedback loop* describes a recursive relationship among system variables in which it is possible for a variable to influence itself over time either directly or indirectly through its effect on other intervening variables (Sterman, 2000). A notable implication of representing a system's dynamics through feedback loops is that distinctions between inputs and outputs become blurred. The circular influence structure inherent in a feedback loop means that any factor, process, or event involved in the cycle can be conceptualized as both an input and an output depending on when it is considered in the sequence of events (Cronin et al., 2011).

For example, Mathieu et al. (2015) describe an empirical study in which they examined the reciprocal relationship between team cohesion and team performance over time. In their data, team cohesion served as an input to performance at time t, but an output impacted by team performance at time $t+1$. The authors observed that increases in team cohesion were associated with increases in team performance, which were subsequently related to increases in team cohesion. This form of recursion exemplifies a *positive or self-reinforcing feedback loop* in which a reciprocal positive relationship exists between two variables in a system (e.g., higher cohesion at time $t \rightarrow$ higher performance at time $t+1$; higher performance at time $t+1 \rightarrow$ higher cohesion at time $t+2$). Positive feedback loops have the potential to compound over time and thus produce explosive patterns of exponential growth or collapse. Alternatively, a *negative or self-limiting feedback loop* is one in which changes in one variable restrict or attenuate changes in another variable over time. For example, DeShon et al. (2004) suggest that individuals working in teams regulate their efforts around accomplishing both individual- (i.e., “I need to type up my daily report”) and team-level (i.e., “Our team needs to deliver the final product by the deadline”) goals. However, in cases where these goals conflict or cannot be accomplished simultaneously, directing efforts towards one goal comes at the cost of effort and achievement relevant to the other goal that must be corrected through future actions (e.g., higher effort towards individual goal at time $t \rightarrow$ lower performance on team goal at time $t+1$; lower performance on team goal at time $t+1 \rightarrow$ reduced effort towards individual goal at time $t+2$). Negative feedback loops result in asymptotic patterns in which changes in the implicated system variables eventually reach an equilibrium. Assuming unlimited time and resources, the feedback loops described by DeShon et al. (2004) would (eventually) result in team members exerting effort towards individual and team goals such that the effort directed towards and performance accumulated on each goal would proceed at rates equivalent to their respective desired level of achievement.

Of note, it is only possible for the sorts of change dynamics depicted above to occur if certain concepts/factors in a system are *dynamic variables* (sometimes referred to as *stocks*, Sterman, 2000). A dynamic variable is one that can maintain its state over time and thus operates as though it has a "memory" of its current state when changing over time (Vancouver & Weinhardt, 2012; Weinhardt & Vancouver, 2012). From this perspective, team cohesion would be considered a dynamic variable as it likely does not exist only at a single time point; it is presumed to exist over and through time such that its level can accumulate or dissipate from moment-to-moment as team members interact or events unfold. The recognition that certain variables/constructs persist and ebb-and-flow in a near continuous fashion is critical to the conceptualization of teams as complex dynamic systems.

The example feedback loops presented above were relatively simple and involved only two reciprocally related variables. However, a feedback loop may be comprised of several intervening elements. For example, Rudolph and Repenning (2002) offer a dynamical systems representation for how "performance disasters" might occur in teams (i.e., team becomes so overwhelmed with tasks that it effectively collapses). In their theory, the number of tasks a team must complete is represented as a dynamic variable such that tasks can continuously accumulate over time and are resolved at a rate equal to the team's capabilities. The authors propose that when faced with a quota of tasks, teams formulate a perception for how quickly those demands can be resolved (number of tasks remaining → perceived resolution rate). This perceived resolution rate subsequently contributes to a team's stress level (perceived resolution → stress), conceptualized as the ratio of a team's perceived resolution rate to its typical resolution rate (e.g., perceiving that more needs to be done than can typically be accomplished increases stress). Lastly, stress is proposed to exhibit a non-linear relationship with how many tasks a team resolves in a given time period such that increased stress improves performance up to a point after which it results in increasingly worse performance (stress → number of tasks remaining).

This (moderately) more complex feedback loop highlights some additional points of interest with respect to representing team phenomena from the perspective of dynamical systems. First, the passage of time is an essential and explicit feature of dynamical systems theories as it permits the transmission of influence among variables/concepts within a feedback loop(s). However, this transmission process need not occur instantaneously and therefore provides a unique way in which substantive concepts or environmental conditions can be incorporated into the representation of team dynamics. For example, including a delay between the arrival of new tasks and when a team becomes aware of those tasks in Rudolph and Repenning's (2002) theory could be used to represent the effect of team situational awareness or the transparency of environmental task demands. Second, dynamical systems representations can incorporate multiple interlocking feedback loops that permit a researcher to explore the combinatorial and opponent processes that commonly exist within real team systems. Although not immediately obvious, Rudolph and Repenning's (2002) theory is comprised of two interlocking feedback loops: (1) a negative/self-limiting feedback loop for when the effects of stress on performance are beneficial (i.e., increased stress → better performance rate → ability to keep up with accumulating tasks) and (2) a positive/self-reinforcing feedback loop for when the effects of stress performance are harmful (i.e., increased stress → poorer performance rate → inability to keep up with accumulating tasks). Lastly, the existence of different and/or different combinations of feedback loops allows researchers to represent and examine the conditions that may give rise to several characteristic types of dynamic patterns. Most notably, dynamical systems theory is particularly well-suited for representing tipping points and periodic/oscillating patterns of system behavior.

Two final concepts gleaned from the dynamical systems perspective that have proven useful for characterizing team dynamics are attractors and perturbations. An *attractor* represents a “state of being” towards which a system evolves over time (Gorman et al., 2017; Nowak et al., 2005). Although there are formal methods for mathematically representing attractors and the “push-pull” they exert on systems, an intuitive characterization of an attractor is that it reflects a point at which a system has converged on a predictable and repeated set of actions, behaviors, and processes given its current conditions. Consistent with the previously discussed notion of steady states, a system and its elements within the domain of influence of an attractor are not necessarily inert. Rather, it means that the sequence of behaviors and interactions within and among system elements and the strength and pattern of cyclical relations among a system’s variables have stabilized, such as when a team has settled into a predictable routine for how its members engage in problem-solving and exchange information.

However, this seemingly stable system behavior may change if conditions change. A *perturbation* represents a “shock” or external disturbance to a system. If sufficiently disruptive, a perturbation may knock a system away from its current attractor state, forcing it to reorganize to enter its previous attractor again or potentially sending it towards a new attractor. Thus, if a change in team membership occurs in which several members turnover and are replaced by new members, the previous sequence of interactions which characterized a team’s communication patterns may change (either suddenly or incrementally) as members establish new preferences and expectations for how to interact. Over time, the team may settle back into the communication structure it used prior to the perturbation or it may transition into an entirely new way of communicating and interacting. Consequently, scientists that apply dynamical systems theories to team phenomena often study and purposefully leverage perturbations in a team’s environment to identify potential attractors that may exist in a team system and the extent to which teams that reside in different attractors function effectively.

Agent-based Systems

In contrast to the dynamical systems perspectives, the agent-based system perspective focuses on explicating how local interactions among specific entities within a collective give rise to more global distributions, patterns, and trajectories produced by a system (Bechtel & Richardson, 1993; Epstein, 1999; Smith & Conrey, 2007). Nevertheless, many of the same concepts (e.g., dynamic variables, feedback loops, perturbations) central to the dynamical systems perspective are represented and captured within the agent-based system perspective as well. However, the explicit focus of agent-based systems on how local occurrences/events give rise to global system properties raises some additional key concepts.

The three most fundamental concepts of agent-based system descriptions are agents, environments, and rules (Wilensky & Rand, 2015). *Agents* are the elementary components/entities of a system that are capable of acting, reacting, or otherwise behaving (e.g., individuals within a team). Agents are described as possessing *attributes* whose levels may be static (e.g., race, sex, personality) or dynamic over time (e.g., perceptions, goals, motivation). In theories rooted in agent-based systems, it is common to consider agents as possessing several attributes simultaneously and to describe the overall "profile" of attribute levels within an agent at any moment in time as the agent's *state*. Consequently, inferences about element- and system-level outcomes from the agent-based perspective often involve interpretations of agent states rather than (or in addition to) aggregate correlations among singular attributes/factors (e.g., which combination of attributes within and between team members contribute to more rapid team cohesion). The initial configuration and subsequent changes in the level and/or distribution of attributes across agents in a system are also typically of interest in agent-based system theories and research (Kozlowski et al., 2013). In this sense, agent attributes both establish the initial conditions of a system as well as provide a continual and recursive source of influence whose effects may change over time.

The second fundamental component of agent-based systems, *environments*, holds a similar connotation as depicted by the previous systems perspectives and characterizes the context in which agents are embedded and interact. However, explications of phenomena from an agent-based system perspective frequently entail efforts to precisely characterize and define specific features of an environment and how they constrain and shape the behaviors/interactions in which agents can engage. Perhaps the most significant such environmental feature in the context of team systems is interdependence. Broadly construed, *interdependence* describes how and/or the extent to which conditions, actors, and/or actions are coupled with (and therefore mutually influenced by) other variables, actors, and/or actions in a system (Weick, 1979). For example, a team task that exhibits a sequential form of interdependence will strongly dictate the order in which the activities and goal-relevant behaviors of individual members are performed (e.g., an emergency medical team needs to establish a patient's airway before directing attention to other bodily injuries; Van de Ven et al., 1976). The structure imposed by this workflow interdependence can subsequently affect how members' social relationships, perceptions, and expectations form by restricting when, which, and how members interact with one another. Relatedly, the environment can also determine how individual contributions to performance are combined to constitute collective system performance (e.g., team sales equal the sum of individuals' sales; speed of a rowing team is determined by the slowest member; Steiner, 1972).

This form of behavioral interdependence can impact how individuals in a team allocate resources, coordinate and organize behaviors, and respond to environmental changes.

The final foundational component of agent-based systems are rules. *Rules* are intended to describe the actions, procedures, and/or mechanisms that individual agents and/or environments enact in response to specific events or conditions (Wilensky & Rand, 2015). Intuitively, the rules specified in an agent-based system elaborate “instructions” that elements of the system “follow” when faced with particular stimuli. In team applications, such rules are analogous to team processes in that they reflect which, when, and to what end individual members engage in behaviors related to task accomplishment (McGrath, 1964, 1984; Marks et al., 2001). The focus on explicating rules that characterize why and how a system’s elements behave is unique to the agent-based system approach. For example, the description of the positive feedback loop between team cohesion and team performance described by Mathieu et al. (2015) conveys how these properties are expected to mutually unfold over time. However, this relationship does not convey what members in these teams are *doing* that would cause these variables to be related and produce a mutually reciprocal pattern. A set of rules such as “members help those they like” and “members like those who perform well” provides one possible generative account for this system-level relationship, but there are likely other rules or rule combinations capable of producing a positive feedback loop between team cohesion and performance. Thus, a critical purpose of explicating rules in an agent-based system is to provide a transparent description of the potential generative mechanisms within a system that enables research to explore how particular patterns of system behavior can arise and be influenced.

Building upon this latter point, an axiom commonly advanced in the broader systems science literature is that “the whole (i.e., a system) is often more than the sum of its parts” (e.g., von Bertalanffy, 1972). Although this mantra is referenced in relation to several different aspects of system behavior, it most generally reflects that a system and its outcomes usually cannot be well understood by only examining its constituent elements in isolation. Instead, understanding system phenomena requires understanding how collective outcomes emerge from the unique actions, relations, and interdependencies among lower-level entities. *Emergence* describes the process through which novel and coherent properties, structures, and patterns arise within a system due to the actions and interactions of the system's constituent elements (Corning, 2002; Goldstein, 1999). Research in the organizational teams literature is replete with examinations of *emergent constructs/states* that reflect discernable "signatures" of stable/emerged behavioral routines, perceptions, and relations (e.g., team performance, team cohesion, team efficacy, team trust, team climates; Kozlowski & Ilgen, 2006; Marks et al., 2001). However, attempting to understand or predict system behavior by focusing only on their emerged properties while ignoring the underlying processes of emergence is akin to trying to infer the plot of a movie by looking only at a single still frame from the film. Consequently, the agent-based systems perspective emphasizes that adequately understanding and impacting emergent system-level properties necessitates explicating the agents, environment, and rules of a system. Through repeated enactment of rules by agents in an environment, unique system characteristics (e.g., team cognition, team norms, team cultures) are created from the "bottom-up." These emergent properties can also subsequently influence behavior and interaction in a more "top-down" manner, thus reflecting the reciprocal "micro ↔ macro relationship" commonly attributed to complex dynamic systems (Page, 2018).

Team Phenomena from an IPO+MLT versus Systems-Oriented Perspective

Although the foci of the open systems, dynamical systems, and agent-based systems perspectives suggest different implications for how one might pursue research, they collectively offer an important foundation upon which to begin developing a more dynamic and actor-oriented view of teams. In the remainder of the paper, we attempt to directly highlight the unique value that this perspective holds for team science by considering how the explication of a specific team phenomena—team performance—might be approached from the conventional IPO+MLT paradigm versus a more systems-oriented approach. To do so, we present and discuss the characteristic features of two models that a researcher might propose to account for team performance. One model is consistent with contemporary treatments of team phenomena, whereas the other adopts a systems-based perspective.

Importantly, the purpose of this discussion is not to develop, articulate, promote, or justify the conceptual rationale of either team performance model. Although we have attempted to make the example models logical and uncontroversial with respect to the team performance literature, the concepts and relations they include are largely irrelevant. Neither representation is intended to advance an account of team performance we advocate be tested or developed in future research per se. Rather, the goal is to highlight how the foci, considerations, rationale, and philosophies underlying the representation of team phenomena (and the accompanying methodologies, inferences, and generalizations they afford) differ when approached from the IPO+MLT (i.e., factor-thinking) perspective versus a systems-oriented (i.e., actor-thinking) perspective. We begin by considering an example model from the more familiar IPO+MLT perspective followed by an example model grounded in a systems-oriented perspective. We then conclude with a summary of some of the strengths and considerations for integrating systems-oriented thinking to advancing team science research.

Factor-Thinking: An IPO+MLT Team Performance Model

Model Description

Figure 1 presents a visual summary of an example model of team performance that might be advanced by a researcher approaching team performance from the IPO+MLT perspective. The model depicts a causal/mediating chain of variables that move unidirectionally from input to process to outcome. The structural relationships reflected in the model suggest that team-level ability and extraversion are expected to be positively associated with team-level task coordination and task communication (respectively). In turn, task coordination and task communication are expected to share positive relationships with team performance and team efficacy. Additionally, the model posits that task complexity moderates the relationship between team ability and task coordination such that the impact of team ability on task coordination is magnified when task environments are complex. Team cohesion is also proposed to be positively related to the level of observed task communication. At the individual level, a single relationship is posited that suggests a member's ability will be positively related to their self-efficacy perceptions. Lastly, the model indicates that the team ability, team extraversion, and team efficacy variables are aggregate constructs of their individual-level counterparts.

Characteristic Features

The exemplar model in Figure 1 highlights several salient features common to models rooted in the IPO+MLT paradigm. First, the model contains multiple constructs specified at different levels of analysis (e.g., individual, team, environment). This conceptual structure is intended to convey that certain variables reside or are only interpretable at a particular level of aggregation within a nested hierarchical system. For example, cohesion is specified as a team-level construct in Figure 1 because it is a property of and is only meaningful for describing teams. Cohesion thus has no meaning or direct interpretation for describing either individual team members or the environment.

Second, the arrows connecting different constructs in Figure 1 are generally intended to reflect the expectation that the antecedent variable will account for some proportion of observed variance in the consequent variable. Thus, the lateral connections from the team-level input variables to the team-level process variables in Figure 1 indicate that the observed level/amount of the former are presumed to covary with the observed level/amount of the latter (and similarly so for the connection between process and outcome variables). In this manner, the structure of the IPO framework shares a strong resemblance with the logic of statistical mediation in which the goal is to convey which variables are associated with (and presumably cause) variation in other constructs. Furthermore, these relationships are commonly conceptualized and described in terms of the simple linear direction of the proposed association (e.g., higher team ability leads to better team coordination which leads to better team performance; Ilgen et al., 2005; Mathieu et al., 2008).

In addition to these feedforward causal paths, there are two other noteworthy relationships reflected in Figure 1 that draw inspiration from the tenets of MLT (Kozlowski & Klein, 2000). The first are *top-down/cross-level relationships* which involve either the direct or moderating effect of a variable situated at a higher-level of analysis on a variable situated at a lower level of analysis. In Figure 1 for example, task complexity (a higher-level environmental input factor) is shown as moderating the relationship between team ability and coordination (a lower-level team input and process variable, respectively). The logic of such top-down relationships is that the higher-level factor in some way “creates” or imposes demands, conditions, etc. that impact how lower-level units function and thus should account for some proportion of the observed variance in lower-level variables. The second type of relationship exemplified in Figure 1 are *bottom-up/emergent aggregations*. These relationships are also cross-level in that the variables of interest are positioned at different levels of the hierarchical system; however, the causal direction is reversed such that the lower-level variable is proposed to compose a higher-level variable. For models rooted in the IPO+MLT paradigm, such bottom-up relationships are generally restricted to characterizing how a construct situated at a lower-level manifests as a functionally similar construct at a higher level of analysis. For instance, Figure 1 depicts a causal arrow from extraversion at the individual to the team level to indicate that team extraversion is a function of individual members' extraversion. However, no causal path can exist between individual-level extraversion and, say, communication at the team-level to represent how a member's extraversion might influence communication within the team. Of note, this restriction is more a statistical limitation of the analytical techniques most commonly used to evaluate factor-based models (Preacher et al., 2010) rather than the inability to conceptually explicate or empirically document the impact of a lower-level unit on a collective system (e.g., Weingart et al., 2010; Kozlowski et al,. 2013)[1]. This point will be briefly revisited in the discussion on systems-oriented models of team phenomena.

A final notable feature of IPO+MLT models is that their modeled constructs and relationships are typically conceptualized as stable, time-independent, and oriented towards inferences between rather than within teams. Consistent with their roots in the factor-thinking philosophy (in which the goal is to examine patterns of covariance among variables), IPO+MLT models of team phenomena seldom acknowledge or attempt to represent that (a) many variables

[1] As an aside, this recognition offers a compelling example of how the analytical/statistical models implemented by the factor-thinking/IPO+MLT researcher have strongly influenced the development of theories and models of team phenomena.

of interest to teams researchers are dynamic, cumulative, and/or emergent (Weingart et al., 2010, Weinhardt & Vancouver, 2012; Vancouver & Weinhardt, 2012; Kozlowski et al., 2013) nor (b) the relationships proposed to exist on average and between teams may not generalize to the dynamic relationships that exist within teams (e.g., Fisher et al., 2018; Molenaar, 2004). With respect to the first consideration and as noted previously in the discussion on dynamic variables, a variable such as team cohesion is unlikely to be a static or time-independent concept. As an aggregate representation of members' experiences, perceptions, etc., it is more akin to a persistent variable that can change over time rather than a static variable whose level is time-invariant[2]. Taken from this perspective, the significance of the second highlighted limitation of the IPO+MLT paradigm can be better appreciated—observing a team's "average" cohesion at a single time point (or even aggregated over a few time points) provides little to no information about how the construct functions or operates within teams.

To elaborate this latter point, Figure 2 demonstrates how the correlation between team cohesion and communication that is proposed to exist in Figure 1 may differ if conceptualized between-team (i.e., measured at a single random time point or averaged over time) versus within-team (i.e., over time). A researcher considering this relationship from the IPO+MLT perspective would typically state that, on average, teams whose members are attracted to one another are expected to exhibit more/richer task communication. This is implicitly reflected in the structural arrow between cohesion and communication shown in Figure 1 and the nature of this covariation is summarized by the larger black-outlined oval in Figure 2. However, a researcher adopting a more dynamic perspective might reason that as team members develop familiarity with one

[2] To the extent a team's cohesion was stable or unchanging over time, it would still be most appropriate to conceptualize the variable as existing in a steady state such that it is continuously "sustained" by the perceptions of individuals' momentary perceptions.

another and their task requirements over time, cohesion may increase while the need for task communication decreases. From this perspective, although teams could differ from one another on their overall levels of cohesion and communication, the association between these variables within-team may be *negative* over time (e.g., gray-outlined ovals in Figure 2). Note that both interpretations can be “empirically correct” in that they could simultaneously exist in observable data. However, only the latter within-team consideration acknowledges or provides insight into how one would expect these variables *actually operate* for a given team.

In other words, the emphasis on between-team thinking commonly reflected in the representation of team phenomena from the IPO+MLT perspective generally fails to consider (or, as in the present example, may promote inferences completely opposite to) how variables and concepts of interest relate to team functioning. There is, of course, nothing which inherently prevents the factor-thinking paradigm from adopting a more longitudinally oriented or within-team perspective. However, the orientation of this perspective towards explicating expected patterns of covariation *on average* among *aggregate variables* lends itself more to considering between-team inferences that generally eschew (or misunderstand; see Cronin et al., 2009) the implications of dynamic variables for drawing causal inferences and advancing generative description about how teams operate.

Summary

The example team performance model depicted in Figure 1 provides an illustrative demonstration of the basic logic and affordances of conceptualizing team phenomena from the IPO+MLT perspective. Owing to its grounding in the philosophy of factor-thinking research (Macy & Willer, 2002), the models and accounts generated under this paradigm are generally directed towards describing expected patterns of covariance among aggregate team-level variables. In so doing, the IPO+MLT approach to teams research implicitly equates explanatory accounts of team phenomena with the extent to which variance in focal team-level outcomes are accounted for by other team-level variables (typically assessed at a single time point). An important and related consequent of this recognition is that the understanding/knowledge of team functioning advanced within this paradigm may only be appropriate for characterizing the strength and direction of relationships that exist on average between teams. The rationale for why and/or the extent to which relationships among important team factors/variables also hold within teams is seldom described or pursued. Lastly, models rooted in the IPO+MLT paradigm do not formally explicate or describe the underlying generative mechanisms and dynamics proposed to account for, or give rise to, observed between- and within-team patterns of covariation. However, this focus is central to the actor- and systems-oriented approach to conceptualizing teams to which we now direct attention.

Actor-Thinking: A Systems-oriented Team Performance Model

Model Description

Figure 3 visualizes an example team performance model consistent with a more systems-oriented perspective. In contrast to the IPO+MLT model of Figure 1, the directional arrows and set of concepts shown in panel A of Figure 3 depict *what* and *how* a team member does, chooses, and/or produces (i.e., process mechanisms) to carry out performance-relevant actions in service of a team's task. Stated differently, Figure 3A summarizes a "blueprint" or "script" that an individual team member is proposed to follow, and which describes what happens as they work towards accomplishing team performance goals. Panel B of Figure 3 highlights that *each* member of the team (i.e., the five circles labeled Members A-E) is proposed to act in accordance with this same script. The lines connecting members in Figure 3B further characterize the potential for the actions/outputs of one member to impact the actions/outputs of (i.e., exhibit interdependence with) of other members as they engage in performance behaviors relevant to accomplishing the overall team task[3].

The core set of generative process mechanisms for the exemplar team performance model are depicted in Figure 3A. The model "begins" with a member contrasting its understanding of the team's task goals to be completed against the current state of accomplishment on those goals. This action results in the realization/awareness of goal discrepancies indicating which tasks still require completion. Next, the individual is posited to choose a task goal on which to focus effort. The arrows leading into the task choice mechanism indicate that this decision is a function of several considerations: (1) the previously computed task goal discrepancies; (2) the individual's preferences for collaborating with other members; (3) the individual's understanding of the demands required to complete each task goal; and (4) the individual's overall self-efficacy. Once this choice is made, the individual directs behavior towards accomplishing the selected goal. As indicated in Figure 3A, the nature of this behavioral expression can be influenced by the task choices of other team members (e.g., if both Member A and Member B elect to work on the same task, the amount of effort directed towards the task may be altered or a different behavioral action performed compared to if only one of these members had chosen to work on the task). This behavioral expression subsequently results in the realization of output that can be operationally defined with respect to task performance (e.g., progress is made on a client report,

[3] Figure 3B presents all members as interconnected and therefore interdependent with one another. However, such a fully connected configuration is not required. For example, a team in which members fulfill specific roles may result in some members being highly connected with others whereas some members exhibit less interdependence (e.g., Humphrey, Morgeson, & Mannor, 2009). Furthermore, the interdependencies among members may be fixed or variable, such as when particular tasks require different subsets of members to collaborate at different points in time to accomplish. To simplify our discussion of the exemplar model in this section, we do not consider these possibilities or their potential generative mechanisms in the text, but simply acknowledge that interdependence networks need not be static or uniform across members in a team.

a widget is produced). Additionally, this model also posits that the degree to which performance output is accrued is affected by the resources available to perform the task as well as the attributes of the individual(s) performing the task (e.g., knowledge, skills, abilities).

The output of this task-relevant performance event is proposed to feed into three subsequent processes for the individual team member. The first involves updating the status of the team's task accomplishments based on the performance outputs generated across all members of the team (cf., Figure 3B). The second process depicted in Figure 3A is task learning. This process is intended to reflect that an individual may develop expertise or task-specific understanding because of their performance efforts that can inform (a) the state of task goals and (b) the demands/requirements for completing a given task. Additionally, the acquisition of task knowledge is posited to affect an individual's perceptions of their self-efficacy. Of note, all three of these consequents are proposed to influence subsequent task choices. The final process depicted in Figure 3A is labeled social learning and is intended to reflect that an individual may develop perceptions of affinity towards their team and other team members through their performance experiences. These affinities form the basis of an individual's cohesion perceptions, which subsequently impact future preferences for collaboration and potentially future task choice decisions. Following these processes, the entire cycle "begins" anew and continues until the team's task goals are completed.

Characteristic Features

The example team performance model summarized in Figure 3 illustrates several unique features of team phenomena conceptualized from a systems-oriented perspective. A first characteristic—and perhaps the most striking in comparison with the IPO+MLT models such as that shown in Figure 1—is that the systems-oriented perspective focuses on identifying and elaborating core concepts and mechanisms relevant to team phenomena from the perspective of the actors and their actions rather than statistical covariation. In this respect, the representation shown in Figure 3 may be more aptly described as a model of team "perform*ing*" rather than a model of team "perform*ance*." Though the model can be used to discuss and/or conceptualize what contributes to team performance, its primary purpose is not to convey the antecedents, moderators, mediators, etc. of this outcome per se. Rather, the model attempts to explicate how and why team performance as a dynamic construct emerges from the behaviors, perceptions, decisions, and interactions of individuals in the team. To facilitate such formulations, it is often helpful to initially approach the development of an actor-oriented/systems-based models by considering how one might "tell the story" about how a phenomenon of interest is proposed to unfold. This strategy encourages the teams researcher to begin thinking through questions that focus more directly on the critical elements of the team as a system, such as:

- Who are the relevant actors? What attributes/characteristics do actors possess which are important to their affective, behavioral, and cognitive responses?
- What exists in the actor's external/operational environment? Which and how do different forces, resources, constraints, etc. in the external/operational environment influence when, which, and why actors may interact, change, and/or react?
- How, where, when, and why might actors interact with other actors and their environment? What actions are the actors able or likely to do in response?
- What are the states in which actors and/or environmental properties can exist over time? Which of these qualities are dynamic versus static over time and why?

Although these questions appear abstract in the absence of any context, their resolution typically becomes more tractable as they are applied to a particular team phenomenon. For instance, the example model in Figure 3 and the verbal description of its operation provided above were generated by attempting to reason through these questions in relation to a generic team performance scenario. In sum, a characteristic feature of models rooted in the systems-oriented perspective is their attention towards which, how, and why the concepts and mechanisms of interest are proposed to emerge and interface with other concepts and mechanisms over time, as opposed to only considering the covariation between sets of static, aggregate, and “already emerged” collective variables.

A second noteworthy characteristic of systems-oriented team models concerns the representation of key variables/concepts important to the explanation for the phenomenon. Compared to IPO+MLT models, there is generally less consideration of whether to categorize variables as input, process, or outcomes or how to ascribe those variables to specific levels of analysis. One reason for this is the variables represented in systems-oriented models often span or fail to adequately fit neatly into such classifications. For example, Figure 3 suggests that an individual’s cohesion perceptions serve as an *input* to collaboration preferences, exist and operate within a social learning *process,* and are an *outcome* of an individual’s affinity towards their other team members and the team. Furthermore, cohesion perceptions are technically situated as an “individual-level” construct in this model because those beliefs are represented as residing with the individual/actor that produces them. However, and as alluded to by Figure 3B, cohesion could be operationalized as a collective (i.e., team-level) property by aggregating members’ cohesion perceptions together if desired.

In addition, the variables represented in systems-oriented models often allow for—or in some cases necessitate—a broader array of operationalizations that can encourage researchers to think about phenomena through new or alternative lenses. The consideration of variables as dynamic, cumulative, and emerging previously discussed as neglected by IPO+MLT models is fundamental to actor-thinking/systems-oriented representations (Kozlowski et al., 2013; Weinhardt & Vancouver, 2012). Furthermore, the conceptualization of variables as dyadic and/or in the context of relational networks is far more common in systems-oriented models. For example, Figure 3 suggests that cohesion is a function of both dyadic/relational perceptions among members (i.e., members' affinities towards each other member) as well as more "gestalt" and/or aggregate perceptions of the team writ large. Explicitly incorporating both representations of cohesion into the same model of team functioning thus encourages future research to consider how and why different patterns of affinity could emerge across both operationalizations and the manner by which they may uniquely or jointly affect member and team outputs.

On a related note, it may seem unusual that the team performance model shown in Figure 3 does not contain any variable labeled team performance. However, the model has several concepts that could be used to conceptualize team performance in unique yet complementary ways. For instance, the performance output variable shown in Figure 3 reflects the amount and/or quality of output produced by a member for a given task at a given time point. Thus, the total performance output generated across all members and tasks at a given time point offers one method for operationalizing team performance. A different representation might rely on task goal discrepancies as this concept captures which, how many, and how much of a team's goals remain to be accomplished. Using this variable, team performance could be conceptualized as the rate of discrepancy reduction within and/or across task goals. Additional ways of conceptualizing team performance in Figure 3 could likely be derived. Although the potential to define a single construct in multiple ways may seem undesirable from the perspective of parsimonious explanation, it acknowledges the reality that many psychological and team-relevant variables are complex constructs that can manifest in different yet informative ways. For example, organizational scholars have long discussed the challenges with developing a straightforward and generalizable definition of performance, highlighting that it can entail different operational definitions (e.g., performance as behavior/action versus outcome/production), foci (task versus contextual performance), and time frames (short-term versus long-term; e.g., Sonnentag & Frese, 2012). The fundamental thrust of the actor-thinking and systems-oriented philosophy to explicate *how* teams function thus recognizes and affords the opportunity to explore the complexities and multifaceted nature of the core variables and constructs involved in team phenomena.

A final distinguishing feature of systems-oriented models are that they attempt to represent team processes as *mechanisms* rather than *variables*. For example, task coordination and task communication are presented as process variables in the IPO+MLT model shown in Figure 1, but would typically be conceptualized as things that a team can do “more/less of” or “better/worse at.” In contrast, task choice, task behavior, task learning, and social learning are presented as process mechanisms in the systems-oriented model of Figure 3. In a fully articulated model (which the example model described in this section is not) these process mechanisms would be precisely specified in a manner that describes *how, what, and when* actions occur.

For this reason, many systems-oriented models are constructed using *computational modeling techniques* rather than through narrative description alone. Although a detailed explanation of these techniques is beyond the scope of the present paper, a computational model is a formal and algorithmic description of how a set of processes are proposed to occur and unfold over time (for general and accessible introductions to computational modeling that are oriented towards organizational scholars, see Davis et al., 2007, Harrison et al., 2007, Weinhardt & Vancouver, 2012, or Vancouver & Weinhardt, 2012). The formalism of a computational model derives from the use of declarative logic (e.g., IF [X ≥ λ], THEN [Y = 1], ELSE [Y = 0]) and/or mathematical equations (e.g., $Y_t = 1/1 + e^{-\lambda*(X_t - X_{t-1})}$) to convey how the core concepts and variables of a system are proposed to change. The algorithmic nature of a computational model derives from declaring the order and sequence in which actions/events are proposed to unfold over time and/or in response to other actions/events which may occur in the system. These elements of a computational model's specification may be informed by conceptual/theoretical reasoning or established through empirical observation. In either case, the end goal is to develop a transparent, precise, and descriptive account of how a system is proposed to operate. Further, most contemporary computational models are translated into computer code and used to conduct simulations and "virtual experiments" that allow one to examine how the proposed set of mechanisms operate under different conditions. This enables the researcher to identify/verify predicted patterns, evaluate the plausibility of potential system outcomes, and design or test "interventions" for influencing system behavior (for examples related to team phenomena in the organizational sciences, see Flache & Mäs, 2008, Grand et al., 2016, or Coen, 2006). Thus, the specification of processes as mechanisms rather than variables in systems-oriented models affords the means for team scientists to precisely describe, explore, and probe how teams function in ways that can promote practical and actionable recommendations for achieving desired team and member outcomes (e.g., McGrath & Tschan, 2007).

Summary

Despite not being a fully developed or articulated model of team performance, Figure 3 offers a useful stimulus for summarizing the characteristic features and underlying philosophy of actor-thinking and the systems-oriented perspective for representing team phenomena. The fundamental orientation of accounts generated within this paradigm are directed towards explicating the activities, events, and interactions that occur within a team system as well as how these mechanisms unfold over time through individual members and their environment. In so doing, the actor-thinking approach promotes conceptualizations and considerations of team phenomena that are targeted towards uncovering and defining core concepts and generative mechanisms of team phenomena that are capable of and/or responsible for producing the emergent patterns, relationships, and properties observed in teams. This focus also permits the potential to generate inferences, predictions, and explanations that are relevant to both between- and within-team generalizations. Lastly, the development of actor-thinking and more systems-oriented models are enhanced through formal model building and evaluation techniques (i.e., computational modeling and simulation). These tools afford researchers the capacity to probe the logic and specification of models, explore multiple and alternative conceptualizations of key variables and outcomes, and develop transparent and precise accounts of generative mechanisms.

Conclusion

Teams and their functioning have long been discussed as operating in a manner consistent with complex dynamic systems (e.g., Arrow et al., 2000; Allport, 1924; Lewin, 1943; Parsons, 1937). However, this conceptualization is seldom reflected in the contemporary theory, methodology, and empirical research on teams in the social, organizational, and managerial sciences. We contend that one cause of this mismatch is that many of the fundamental tenets, ideas, tools, and orientations embodied by systems science are unfamiliar and/or their significance greatly undervalued by team scientists (Epstein, 1999; Gorman et al., 2017). The goal of this paper was to introduce several key concepts across the diffuse and eclectic domains of systems science and demonstrate their application for conceptualizing and researching team phenomena. Additionally, key features of models developed within the currently predominant factor-thinking paradigm (which draws heavily from the IPO framework of team functioning, McGrath, 1964, and the meta-theoretical and methodological recommendations of MLT, Kozlowski & Klein, 2000) and those rooted in an alternative actor-thinking paradigm (which draws heavily from the principles of complex, dynamic, and adaptive systems, von Bertalanffy, 1972) were summarized to highlight the unique differences and foci these approaches hold for considering collective phenomena (Macy & Willer, 2002).

We contend that the perspective advanced by adopting a more systems-oriented approach holds significant promise for advancing the state of team science. Most significantly, this approach draws attention towards explicating *how* teams function, interact, and exert/experience influence from their environments by considering *what, when, and why* team members "do" when working within teams (Kozlowski et al., 2013). The identification and specification of these generative mechanisms affords team researchers the potential to more precisely explicate and directly explore how the dynamic patterns and emergent properties of teams unfold as well as how those properties are produced and thus can be impacted (Epstein, 1999).

Lest one conclude that the actor-thinking and systems-oriented perspective is a panacea for team science, there are some noteworthy challenges and likely obstacles with adopting this approach that are worth recognizing. The inherent complexities of considering both the intra-and inter-individual dynamics that occur within teams means that more systems-oriented models can easily become complicated, cumbersome, and onerous to comprehend if not appropriately restricted. Additionally, the temporal scale for many team phenomena is both poorly understood and likely to differ across constructs, contexts, and member configurations. Consequently, although actor-based and systems-oriented models can be developed and readily used to propose potential trends, trajectories, and/or patterns of team outcomes, predicting the actual or required durations for such developments to occur is difficult. Additionally, and as alluded to when describing the features of the example model in Figure 3, most representations of team functioning rooted in this perspective must be translated into formal quantitative/computational models to fully articulate and examine how they operate (e.g., Cronin et al., 2009). We do not believe this a limitation of the actor-thinking and system-oriented approach per se; on the contrary, the development of more precise, transparent, and rigorous theory would be a boon for team science (Cronin et al., 2011; Kozlowski et al., 2013). However, it does entail a skillset (i.e., computer modeling/programming, expressing propositional statements in formal logic and mathematical equations) for which many social and organizational scientists do not receive training. Nevertheless, the potential of embracing a more dynamic and actor-oriented view on teams far outweigh these potential obstacles. Through attempting to realign team science with its origins in systems thinking, we believe the discipline can be propelled into a vibrant and impactful future.

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Figure 1

Example Team Performance Model Consistent with a Factor-thinking/IPO+MLT Perspective

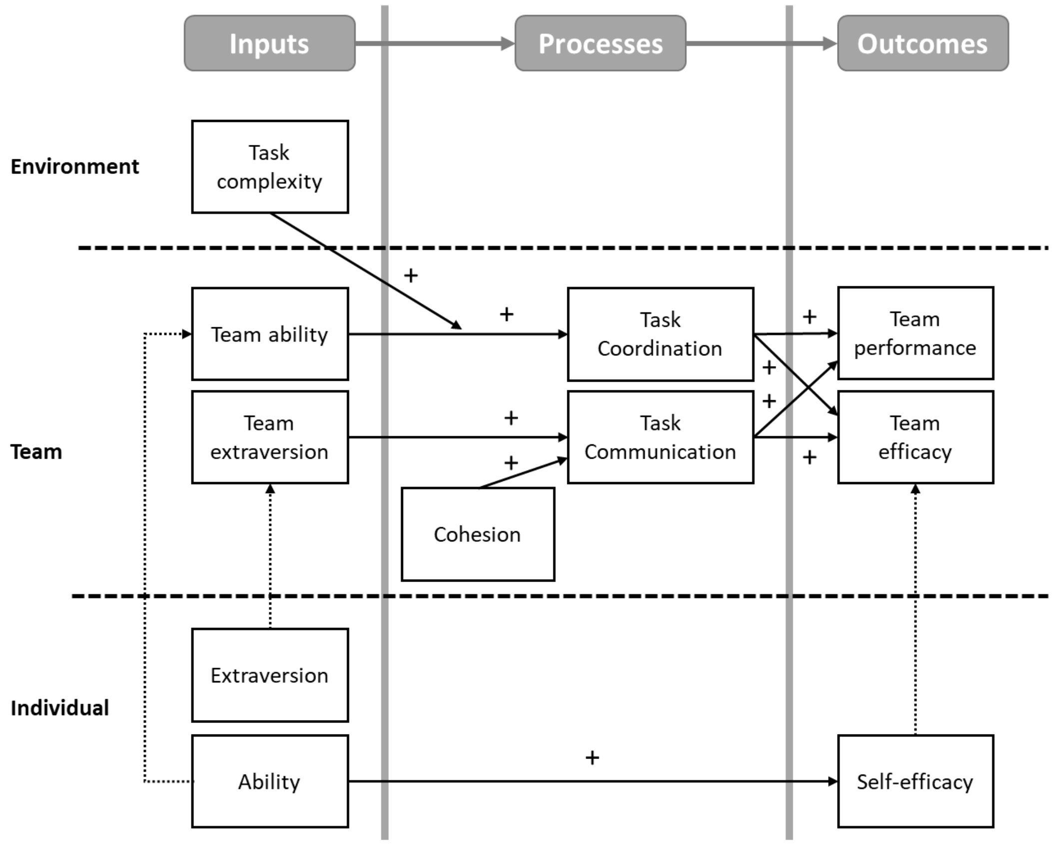
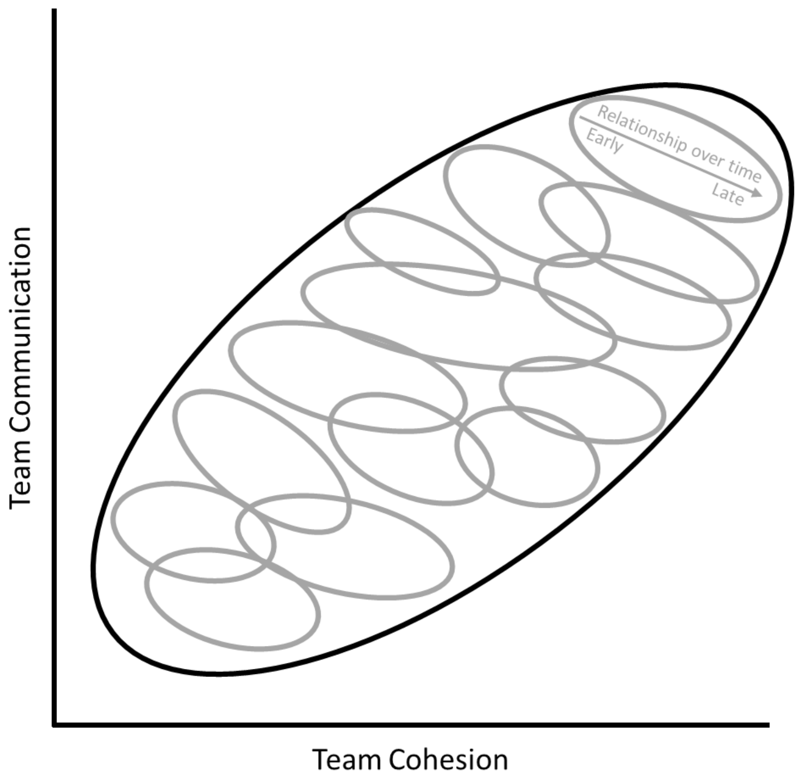


Figure 2

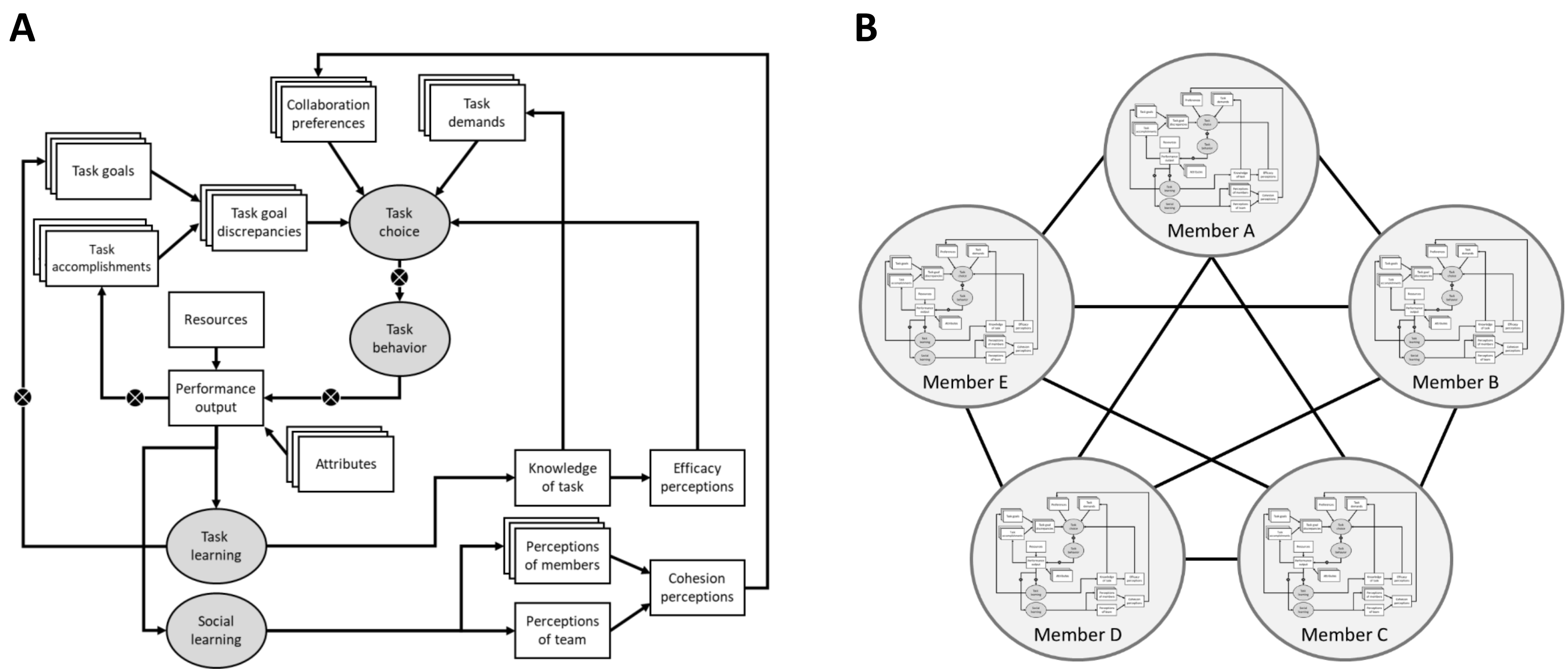
Demonstration of the Potential for Differences in the Correlation Between Team Cohesion and Task Communication When Considered Within- Versus Between-teams



Note. The larger, black-outlined oval represents a between-team relationship between team cohesion and task communication calculated by assessing teams' data on both variables either at a single time point or averaged over time. The smaller, gray-outlined ovals represent the within-team relationship between team cohesion and task communication observed for several teams based on observations of both variables over time. The annotation in the figure indicates that the within-team relationships are negative because the relationship between team cohesion and team communication decreases from earlier to later measurement periods.

Figure 3

Representation of the Generative Mechanisms (A) and System-level View (B) of Example Team Performance Model Consistent with an Actor-thinking/Systems-oriented Perspective



Note. In panel A, shaded gray circles reflect process mechanisms, stacked boxes reflect that the construct is represented by a vector of values rather a single value, and black circles with a cross reflect where the actions/outputs of a team member can be impacted by the actions/outputs of other team members (e.g., the task choice of Member A can impact the task behaviors of Member B). In panel B, each member is shown as adhering to the same generative mechanism model depicted in panel A, with the solid lines connecting members reflecting the potential for interdependence among the actions/outputs of team members.