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Flock Leadership: Understanding and influencing emergent collective behavior

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ABSTRACT

This study introduces Flock Leadership, a framework for understanding and influencing emergent collective behavior in the context of human organizing. Collective capacities emerge when interactions between individuals enact divergent and convergent ways of perceiving and responding to reality. An agent-based flocking model is employed to represent these interactive dynamics and emergent processes. This study explicates the model's constructs, translating its algorithms into behavioral norms at the individual level and its outcomes into collective behaviors at the group level. Phenomena-based simulation modeling links two collective states—technical capacity and adaptive capacity—to the specific underlying norm configurations from which they emerge. Flock Leadership provides a unique theoretical framing of emergent collective behavior in organizational settings, a new methodology for analyzing relationships between those emergent behavioral patterns and the interaction norms underlying them, and a useful means for identifying leadership opportunities.

"The hallmark of a great leader is that when he is gone, people say 'we did it ourselves'".–Lao Tsu.

Austrian-born conductor Herbert von Karajan (1908–1989) led the Berlin Philharmonic Orchestra with restraint. Uncomfortable with von Karajan's limited and imprecise gestures, a trumpet player once asked, "Maestro, with all due respect, when should I start playing my tune?" Von Karajan responded, simply and pointedly, "when you feel it's the time." A journalist, similarly mystified, questioned the conductor, "Maestro, why don't you give precise indications to your orchestra?" Von Karajan's answer revealed the basis of his leadership approach: "Because," he explained, "that's the worst damage I could do to them: the musicians would not listen to each other" (Cousin, 2012, para. 7). Von Karajan underscored the *listen to each other* norm during rehearsals. He would simply point his baton at a single player, a gesture intended to tell the other players 'listen to him', explains von Karajan biographer Richard Osborne. "When the playing of the rest of the orchestra complemented that of the solo", continues Osborne, "von Karajan would give a thumbs up and move on" (Tyner, 2001, para. 1). Israeli conductor Itay Talgam describes the influence of von Karajan's restraint on the orchestral collective: "They look at Karajan. And then they look at each other. 'Do you understand what this guy wants?' And after doing that, they really look at each other, and the first players of the orchestra lead the whole ensemble in playing together" (Talgam, 2009, para. 17).

Von Karajan could have commanded his orchestra to look to him; he was the conductor, after all. Why, then, did he encourage them to look and listen to one another? Von Karajan understood the potential for interacting parts to self-organize into a coordinated, energized whole. He saw his leadership role as creating space for the parts to interact while guiding and ingraining the norms of interaction. The resulting harmony was an emergent property of the orchestral collective, meaning that it arose as a

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result of the interaction of the players and that it was not a property of any of the players individually. Emergent collective behaviors have varying degrees of predictability (Marx & McAdam, 1994). The collective behavior guided by von Karajan was relatively predictable; when his Berlin Philharmonic played Mozart's symphony no. 31, for example, concert-goers familiar with the score could anticipate the essential content of the production. Von Karajan expected that honing the norms of listening and interaction would generate better emergent harmony, not novel content.

Managers and leaders in other contexts have very different expectations of the collective behaviors they oversee. Some organizations look to emergent collective behavior not to navigate the known and refine the present but to discover the unknown and create the future. One such organization is Pixar Animation Studios, whose president, Ed Catmull, underscores the importance of interaction when he describes the consequences of changing the site of creative meetings from a long skinny table to a smaller square table: "Sitting around that [smaller square] table, the interplay was better, the exchange of ideas more free-flowing, the eye contact automatic. Every person there, no matter their job title, felt free to speak up" (Catmull, 2014, p. 3). Like von Karajan, Catmull wants members of his team looking and listening to each other. At the Berlin Philharmonic, interaction drove emergent collective harmony; at Pixar, interaction drives emergent collective creativity.

The von Karajan and Catmull insights establish several themes and suggest several questions central to analysis of emergent collective behavior in organizational contexts. There are different types of emergent collective properties and behaviors. What, then, are the principal types and how do those types relate to the challenges organizations face? In particular, how does the collective capacity necessary for incremental improvement at familiar tasks differ from that necessary for discovery and transformation? By definition, emergent collective behavior cannot be commanded and controlled. It is nonlinearly related to interactions between numerous individuals, not the direct result of authoritarian dictate. What, then, constitutes leadership in the context of emergent collective behavior? How might one exercise influence without invoking and exerting formal authority? If emergent collective behavior is a function of interactions between individuals, then what can we learn about *how* different interaction norms on a team, in a department, or throughout an organization generate different collective behaviors?

These questions motivate this study, which introduces a framework for understanding and influencing emergent collective behavior that I call *Flock Leadership*. To develop insights into Flock Leadership, I employ an agent-based flocking model to represent the process by which human collective capacity emerges. As numerous scholars discuss (e.g., Davis, Eisenhardt, & Bingham, 2007; Dinh, Lord, Gardner, Meuser, Liden & Hu, 2014; Harrison, Lin, Carroll, & Carley 2007; Uhl-Bien, Marion, & McKelvey, 2007), agent-based computational modeling is well-suited to analysis of emergent behavior in complex systems because it accommodates the interactivity, nonlinearity, and multi-level processes characteristic of emergence. Inspired by the emergent collective behavior found in schools of fish, herds of land animals, and flocks of birds, agent-based flocking models consist of algorithms reflecting the simple movement rules underlying complex aggregate motion (Goldstone & Gureckis, 2009). A defining property of flocking models is that component individuals base their movement decisions on the behaviors of their peers. Thus, collective movement patterns emerge from localized interactions between neighboring individuals, not from the orchestrated design of a leader or central authority.

In the sections below, I situate Flock Leadership in relation to existing analyses of emergent collective behavior in the leadership literature, explain why agent-based simulations are useful tools for analyzing emergence, and introduce the flocking model that serves as the basis of this study. Next, I explain how I interpret the flocking model to represent organizational dynamics. This entails translating the model's algorithms into behavioral norms at the individual level and translating the model's outcomes into collective behaviors at the group level. I then conduct phenomena-based simulation modeling for the purpose of analyzing relationships between interaction norms and patterns of collective behavior. What configuration of behavioral norms generates collective capacity for incremental improvement at familiar tasks, which I call *technical capacity*? What configuration of behavioral norms generates collective capacity for discovery and transformation, which I call *adaptive capacity*? I close with a discussion of the implications of Flock Leadership for theory, research, and practice. Flock Leadership provides a novel theoretical framing of emergent collective behavior in organizational settings, a new methodology for analyzing relationships between those emergent behavioral patterns and the interaction norms underlying them, and a useful means for identifying leadership opportunities.

Emergent collective behavior and leadership

This study defines collectives as McGrath, Arrow, and Berdahl (2000, p. 95) define groups: as "bounded, structured entities that emerge from the purposive, interdependent actions of individuals." The behavior of a collective is said to be emergent when it arises from interactions among a set of individuals, when it assumes distinct patterns, and when it cannot be understood simply as the sum of its constituent parts (Pais, 2012). A set of individuals that exhibits emergent collective behavior is known as a complex adaptive system. It has become increasingly popular in the past two decades to view groups of people (McGrath et al., 2000) and, more broadly, organizations as complex adaptive systems, or "dynamic systems of adaptation and evolution that contain multiple parts which interact with one another and the environment" (Morel & Ramanujam, 1999, p. 278). It makes sense, in part, to approach groups of people as complex adaptive systems because of the pivotal role that *interaction* plays in influencing behavior in both contexts. "The central feature," writes Joseph McGrath (1984, p. 13), "the 'essence', of a group lies in the interaction of its members—the *behaving together*, in some recognized relation to one another, of two or more people who also have some past and/or future relation to each other." In complex systems, even though interactions between elements may follow relatively simple rules, feedback loops generate nonlinear outcomes in the form of patterned emergent behaviors at the collective level (Anderson, 1999). The study of such systems has acquired the name complexity theory, though it is less a single theory than an interdisciplinary ensemble of approaches modeling how microstate events self-organize into emergent aggregate structures (McKelvey, 1999). The various approaches to complexity theory share the following points of emphasis: a systems-level perspective; attentiveness to the interaction of component parts; interest in the ways in which an emergent systemic whole is different than the sum of its parts; and focus on processes that underlie nonlinear relationships between individual-level occurrences and collective outcomes.

Leadership in complex organizations

The leadership literature's first extended engagement with complexity theory was authored by Marion and Uhl-Bien (2001). Complexity theory, explain the authors, highlights the limitations of the leadership field's traditional reductionism (a research approach in which parts of a system are isolated and studied independently of the system from which they derive) and determinism (the belief that by knowing preceding variables one can predict the future with certainty) (Marion & Uhl-Bien, 2001, p. 391). Because it highlights nonlinearity and the reality that emergent collective properties are frequently quite different from the aggregate of a system's individual properties, complexity theory demands a more holistic approach that understands leadership as systems influence rather than interpersonal influence. From a complexity theory perspective, observe Marion and Uhl-Bien (2001), leadership effectiveness depends not upon *controlling* the future, but rather upon fostering interactive conditions that *enable* a productive future. Effective leadership begins with an understanding of the general contours of relationships between interactive dynamics and patterns of collective outcomes. Exercising leadership is about creating conditions that promote the emergence of collective behaviors appropriate to the challenge at hand. "Complex leaders," explain Marion and Uhl-Bien (2001, p. 394), "understand that the best innovations, structures, and solutions to problems are not necessarily those that they, with their limited wisdom, ordain, but those that emerge when interacting aggregates work through issues."

The observations set forth by Marion and Uhl-Bien (2001) provide a foundation from which they and other authors explore more specific implications of complex systems leadership. Research focuses on ways that leaders can create conditions for productive interaction and emergence. There is general agreement that certain interactive dynamics promote the generation of diversity—meaning diversity in priorities, beliefs, habits, loyalties, cognitions, perspectives or routines—and that other dynamics reduce diversity and promote collective consensus. Most authors exploring implications of complexity theory for leadership convey the need for leaders to achieve some sort of *balance* between diversity and consensus or—stated more broadly—balance between disorder and order. Some studies describe leadership efforts to achieve continuous, incremental change by maintaining an ongoing balance between order and disorder dynamics (Lichtenstein, Uhl-Bien, Marion, Seers, Orton, & Schreiber, 2006; Marion & Uhl-Bien, 2001; Schneider & Somers, 2006; Uhl-Bien et al., 2007). Other studies describe less frequent, more revolutionary change that emerges from a looping order–disorder–order process involving the following four sequential stages: dis-equilibrium onset, amplification dynamics, stabilization dynamics, and recombination dynamics (Lichtenstein & Plowman, 2009; Plowman, Solansky, Beck, Baker, & Kulkarni, 2007).

The groundwork has been laid for a complexity theory approach to leadership. Opportunities remain, however, to build on the theoretical foundation that has been established. In particular, there is a need for more precision regarding which interactive dynamics should be promoted, in what measure, and for what purpose. In their overview and analysis of collectivistic leadership approaches, Yammarino, Salas, Serban, Shirreffs, and Shuffler (2012, p. 392) note the need for research "determining what factors contribute to a particular type of complex adaptive system." If effective leadership entails creating conditions conducive to the balance of diversity- and consensus-generating interactive dynamics that in turn yield emergent collective behaviors, this central question remains: *what does that balance look like*? Furthermore, how should the look of that balance *vary* depending upon whether our collective seeks incremental improvement at familiar tasks, or discovery of new cognitions, perspectives, and processes? For example, Marion and Uhl-Bien (2001) contend that exercising leadership in complex organizations entails fostering conditions conducive to diversity generation by "dropping seeds of emergence," while fostering as well conditions conducive to consensus formation by building networks and enabling others to build networks, and by serving as "tags", their term for symbols of the philosophy that binds together the collective. However, an organizational participant seeking to exercise complex leadership might reasonably ask the following: *In what measure* should the various conditions be enabled? *How strong* should the different enabled interactive dynamics be? Should the mix of enabling conditions and resulting interactive dynamics *vary* according to the collective capacity desired? Similarly, Uhl-Bien, Marion, and McKelvey (2007) contend that exercising complexity leadership revolves around enabling three conditions they call tension, interaction, and interdependency, but their discussion again begs the question: *What measure* of each should be fostered given the collective behavior desired?

Why computer simulation?

Computer simulation methods in general—and agent-based flocking models in particular—have unique potential to advance theory and bring greater precision to analyses of complex dynamics in the context of leadership. While mathematical tractability limits the capacity of traditional statistical approaches to accommodate interactivity and nonlinearity, computer simulation has the potential to provide superior theoretical insight into complex systems behavior (Davis et al., 2007; Harrison et al., 2007). Simulation methods are particularly valuable means of theory development in certain research contexts. The study of leadership in complex systems, I contend, contains three key contextual attributes that scholars identify as ideal for simulation methods. First, simulation methods are especially useful in developing simple theory, meaning "theory that has only a few constructs and related propositions with modest empirical or analytical grounding" (Davis et al., 2007, p. 482). Simple theory contrasts with well-developed theory, such as institutional theory or transaction cost theory, where constructs are clearly defined, theoretical propositions have received extensive empirical grounding, and theoretical logic is well elaborated. Simple theory "includes basic processes that may be known... but that have interactions that are only vaguely understood, if at all" (Davis et al., 2007, p. 482). I contend that the theory associated with complex systems leadership is simple theory, and therefore stands to benefit from computational modeling. Second, simulation is particularly valuable "when the focal phenomena involve multiple and interacting processes, time delays, or other nonlinear effects such as feedback loops and thresholds" (Davis et al., 2007, p. 483). Simulated variations in conditions can disclose discontinuities or bifurcation points resulting from nonlinearities in interactive systems (Harrison et al., 2007, p. 1235). Complex systems leadership involves multiple interacting processes generating nonlinear collective outcomes, and therefore is an appropriate topic for computational modeling. Third, simulation is highly useful for theory development when a research question involves a fundamental tension or trade-off. Such tensions "often result in nonlinear relationships, such as tipping point transitions and steep thresholds... (which) are difficult to discover using inductive case methods and difficult to explore with traditional statistical techniques" (Davis et al., 2007, p. 485). As I shall show, two fundamental tensions affect the exercise of leadership in complex systems, making it fit for computational modeling: the diversity-consensus tension at the individual level of analysis, and the technical capacity–adaptive capacity (or exploitation–exploration) tension at the collective level of analysis.

Why a flocking model?

Agent-based computer simulations are distinctive in that they model individual behaviors rather than describe a system only with variables representing the collective (Railsback & Grimm, 2012). Flocking models are a specific variety of agent-based simulations that are designed to capture the collective behavior of numerous interacting autonomous agents (Reynolds, 1987). Flocking models spatially detail the structure of individual-individual relationships residing at the heart of collective behavior. Agents are autonomous in that they make their own decisions but interconnected in that their decisions depend upon peer behaviors. Information on neighbor behavior is processed into individual behavioral decisions through interaction rules reflecting inclinations to separate from, to align with, and to move toward local peers (Lemasson, Anderson, & Goodwin, 2009). Though commonly used by robotics engineers and scholars of animal behavior (Leverentz, Topaz, & Bernoff, 2009), flocking models have yet to be employed by leadership or organizational scholars. They are highly appropriate to analysis of complex systems because they are explicitly multilevel; they link interactions between individuals to collective outcomes. For this reason, the application of flocking models to organizational contexts answers the calls that prominent scholars have long made for more attention to be paid to interactive processes underlying collective outcomes. For example, noting that "the structure of collective constructs is composed of the actions and interactions of organizational members," Morgeson and Hofmann (1999, p. 256) conclude that "attention needs to be given to studying and understanding the nature of this interaction." In a similar vein, Drazin and Sandelands (1992, p. 231) "argue that the process of organizing can best be modeled at the level of observed actions and interactions of individuals." Flocking models have unique potential to bring greater precision and specificity to analysis of complex leadership dynamics because they are designed to measure the strength of the "rules" governing agent–agent interactions. The models enable users then to link specific collective behaviors to specific configurations of agent–agent interaction "rules". The level of specificity associated with these models facilitates the development of a particular type of complex systems leadership theory that I call Flock Leadership theory.

Flock Leadership theory explores how different collective learning capacities emerge when interacting individuals work through challenges. It models collective learning—understood as changes in ways of perceiving and responding to reality—as movement through two-dimensional space. There are precedents for learning-as-movement models in both the management and the psychology literatures. In the former, NK modeling studies conceptualize human perception and response as movement through physical space. Developed by Kauffman (1993) to analyze the role of complexity in biological systems, NK computational models have been used widely by organizational scholars to study such concerns as adaptation (Levinthal, 1997), search (Gavetti & Levinthal, 2000), design (Rivkin & Siggelkow, 2003), and technological innovation (Fleming & Sorenson, 2001, 2003). In NK models, managers make decisions that move their organizations, or the products their organizations sell, through three-dimensional landscapes to more or less fit locations. Fitness landscapes are characterized by varying degrees of smoothness and ruggedness depending upon the level of interdependence between component parts of the organization or product being studied. While NK models are useful for estimating the proximity of existing organizational and product configurations to more optimal configurations, they do not analyze the collective search and learning dynamics that managers must understand to navigate fitness landscapes. Decision-makers in NK models learn over time which combinations of organizational or product components enhance effectiveness, but the individuals within teams or organizations do not learn *from each other*. The Flock Leadership framework addresses this gap by highlighting interactive learning dynamics.

Collective search and learning dynamics have been simulated in the psychology literature, where Gabora and Saberi (2011) model the development of collective creativity as agent movement through two-dimensional space. The authors use as their starting point the basis of human learning, which is that "one thought or idea evokes another, revised version of it, which evokes yet another, and so forth recursively" (Gabora & Saberi, 2011, p. 300). Their model revolves around three core elements of collective cognitive development: individual invention, peer evaluation, and peer imitation. These three elements approximate the inclinations of agents in flocking models to separate from, to align with, and to move toward local peers. Gabora and Saberi (2011, p. 300) seek, as does the Flock Leadership model, to capture "the process by which ideas adapt and build on one another in the minds of interacting individuals." Despite its similarities to the Gabora and Saberi model, the Flock Leadership framework is uniquely suited to exploring emergent collective behavior in contexts of human organizing. Each agent in the Gabora and Saberi model interacts with only one other agent at a time, meaning that the resulting group learning is summative rather than emergent. Flock Leadership theory is thus distinct in exploring multi-agent interactions of the type that occur in organizational collectives, and linking those interactions to emergent, nonlinear consequences.

Modeling Flock Leadership

In this section, I introduce the model that serves as the basis of my Flock Leadership theory development. I describe how the model operates, then translate it to the context of human organizing by explaining how I interpret its algorithms as interaction norms at the individual level and its outcomes as collective behaviors at the group level.

The NetLogo flocking model

Agents in flocking models base their movement decisions primarily on three simple behavioral rules (Reynolds, 1987). The rules reflect tendencies to separate from, to align with, and to cohere with (i.e., move toward) peers with different positions and directional orientations. The simulations analyzed in this study are run using NetLogo's (Wilensky, 1999) flocking model (Wilenksy, 1998), which operationalizes behavioral rule strength with the measure "turn angle." Thus, the relative strengths of separation, alignment, and coherence tendencies within a collective are represented with the parameters *max-separate-turn*, *max-align-turn*, and *max-cohere-turn*, where each parameter reflects the maximum angle that an agent can turn as a result of each rule during one simulation iteration. Turn angle parameters range from zero to twenty degrees, with larger values indicating stronger behavioral inclinations. In addition to the three turn angles, the NetLogo flocking model contains the parameters *minimum-separation* and *vision.* Minimum-separation indicates the minimum distance of separation that two agents attempt to maintain (Stonedahl & Wilensky, 2010). The parameter ranges from zero to five patches. Minimum-separation is distinct from max-separate-turn in that the former is a threshold distance measure, while the latter is a continuous variable reflecting the relative strength of an agent's inclination to avoid its nearest neighbor. The vision parameter indicates the maximum distance, measured from zero to ten patches, that an agent is capable of sensing peers. Different configurations of separation, alignment, coherence, minimum-separation, and vision norms govern different collective outcomes. For example, agents abiding by one set of norms may occupy dispersed positions but align their directionality closely with peers, generating linear, predictable net motion, while agents in another group may crowd together and align their directionality, generating curvilinear net motion with a constantly changing trajectory.

Translating the model: interaction norms

The various elements of NetLogo's flocking model—the two-dimensional space, the interaction rules, the collective outcomes—have analogues, I contend, in the context of human organizing. I now translate into human terms the two-dimensional space through which simulated agents move, then in subsequent sections propose human behavioral correlates to NetLogo's interaction rules and collective outcomes.

Agents in flocking models move through patches of two-dimensional space. At any particular point in time, an agent has both a position and a heading. An agent's position at time T_x is its *xy* location, while its heading is the direction from its *xy* location at T_x to its *xy* location at T_{x+1}. Heading reflects and extends an agent's historical trajectory of *xy* locations at T_{x-1}, T_{x-2}, T_{x-3}, and so forth backward in time. In contexts of human organizing, our interest is not in how individuals relate to one another physically, but rather how they relate to one another cognitively and emotionally in the course of collectively working through a challenge such as an ethical dilemma, a product design concern, a process quality problem, and so forth. Accordingly, I treat each patch of two-dimensional space as a distinct *interpretation* of whatever challenge confronts the human collective in question. I define interpretation as "a way of perceiving and responding to reality" (Heifetz, Grashow, & Linsky, 2009, p. 118). Thus, the flocking model represents emergent collective movement through different interpretations over time.

At a given point in time, an individual has both an *interpretative position* and an *interpretative heading*. I define interpretative position as the bundle of cognitions and perspectives that comprise an individual's way of perceiving and responding to reality at a point in time. I define interpretive heading as the historical and anticipated trajectory in the development of an individual's way of perceiving and responding to reality over a period of time. Both constructs are relational. An individual's interpretative position can be identical, proximal, or distal to the interpretative positions of neighboring individuals. An individual's interpretive heading reflects the consistency, predictability, and direction of the development of that individual's way of perceiving and responding to reality, which can be more or less aligned with the interpretive headings of neighboring individuals. The external environment in which the collective operates and with which it interacts is represented indirectly rather than directly in the flocking model. Outside stimuli are mediated though individual perceptions and responses. In other words, the environment is expressed through its influence on individual cognitions and perspectives.

Just as interaction rules govern agent behavior in the flocking model, group norms govern human behavior in many group contexts. While scholars define group norms in subtly distinct ways, most agree that they are, in essence, shared behavioral rules. Feldman (1984) defines norms as the informal rules that groups adopt to regulate and regularize group members' behavior; Thibaut and Kelley (1986) define them as behavioral rules that are accepted, at least to a large extent, by a sizable number of people in a group; Voss (2001) defines them as behavioral regularities in a group of actors; Interis (2011) defines them as voluntary behaviors that are prevalent within a given reference group; and Gonzalez-Mule, DeGeest, McCormick, Seong, and

Brown (2014) define them as informal, shared standards against which the appropriateness of behaviors in groups is evaluated. As shared behavioral rules, group interaction norms operate in human contexts as interaction rules operate in the flocking model. I now turn to translating NetLogo's five interaction rules into human behavioral correlates. Table 1 matches human interaction norms with associated model variables:

Uniqueness norm

The max-separate-turn parameter measures the strength of an agent's tendency to move its position away from the position of its closest peer. It reflects an agent's inclination to follow the coding command "turn away (from) heading of nearest-neighbor" (Wilensky, 1998). The higher the max-separate-turn value, the further an agent will move its position away from the position of its closest flockmate. Thus, the parameter reflects agents' comfort level with holding positions far removed from one another. In some simulated collectives positional diversity is a strong norm, while in other collectives agents exhibit little inclination toward positional heterogeneity. Similarly, human collectives differ from one another in the extent to which they enact diversity in ways of perceiving and responding to reality (Bechtoldt, De Dreu, Nijstad, & Choi, 2010). We can say that a group has a strong *uniqueness norm* if its members generate many diverse interpretations. I define the interaction norm *uniqueness* as the strength of an individual's tendency to develop her own unique ways of perceiving and responding to reality. This definition reflects scholarship showing that the need for distinctiveness—the need to feel like a differentiated individual—is a fundamental human drive (Brewer, 1991; Hornsey & Jetten, 2004). In their study on the role of distinctiveness in identity formation, Vignoles, Chryssochou, and Breakwell (2000, p. 346) conclude that "a pervasive human motivation exists to see oneself as distinctive, which derives from the importance of distinctiveness for meaningful self-definition." While the desire to feel unique may be fundamental and pervasive, individual differences in uniqueness needs have been demonstrated as well (Tepper & Hoyle, 1996). Individuals are most likely to manifest a strong uniqueness norm when they are high in desire, ability, and opportunity to develop unique ways of perceiving and responding to reality. They might engage in the following representative behaviors: showing a commitment to originality; maintaining independent judgment; jockeying competitively with peers to be (and to be seen as) the smartest, the most creative, or the best educated; and thinking like a "Devil's advocate", routinely questioning dominant or reigning interpretations.

In order to add depth and texture to my descriptions of the norms introduced in this section, I will include a series of hypothetical vignettes set in an organizational context. Consider an organization in the process of implementing a new strategic position. This hypothetical organization is a small liberal arts college in the United States, and the new strategic position is "Global College." The collective whose norms we will consider is the faculty. First imagine a faculty with high uniqueness norms working through the curricular implementation of this new strategic position. This faculty generates a variety of perspectives on what "global" means and entails in this context. Some members regard the term as synonymous with international; others understand it to mean interconnectedness. There are divergent perceptions of what makes a "Global College" global. Some professors consider a large range of foreign language courses a necessity. Others emphasize the need for numerous study abroad opportunities. Calls are made for a high proportion of international students in the student body and for a large proportion of international professors in the faculty. Certain professors suggest an emphasis on curricular inter-disciplinarity to underscore interconnectedness. For some, global means a large number of courses in the international relations discipline, while for others it entails that each course across the curriculum, regardless of discipline, explores global implications in some way.

What accounts for the high uniqueness norm in this hypothetical faculty collective? It may have multiple causes. The inclination toward independent thought is likely a professional norm for professors. In this organization specifically, there may be an expectation that professors make singular, valuable contributions to college strategy and policy. Perhaps it is understood that social esteem and peer respect accrue to individuals who demonstrate intelligence, experience, insight, creativity, eloquence, and passion. The uniqueness norm can be weak as well as strong. The process of implementing a "Global College" strategic position at a college with a low uniqueness norm feels quite different. Professors are content to *not* generate a multitude of perspectives on what global means and entails. The expectation in this context is that teachers teach and administrators make and implement strategy. Professors are comfortable entrusting strategic decisions to the dean's office or a college task force. Or, the professors do not proffer unique opinions on the matter because they are over-worked and exhausted, because they are

Table 1.
Interaction norms and associated model variables.

Interaction norms	Associated model variables
Uniqueness norm: the strength of an individual's tendency to develop her own unique ways of perceiving and responding to reality	Max-separate-turn: the strength of an agent's tendency to move its position away from the position of its closest peer
Communication norm: the level of an individual's effectiveness at communicating with her peers about her and their ways of perceiving and responding to reality	Max-align-turn: the strength of an agent's tendency to align its heading angle with the average heading angle of its peers
Consensus norm: the strength of an individual's tendency to forge with her peers shared ways of perceiving and responding to reality	Max-cohere-turn: the strength of an agent's tendency to move its position toward the average position of its peers
Peer exposure norm: the extent to which an individual is exposed to her peers' ways of perceiving and responding to reality	Vision: the distance that an agent is capable of sensing peers
Conformity intolerance norm: the strength of an individual's tendency to resist her peers' ways of perceiving and responding to reality	Minimum-separation: the minimum distance of separation that two agents attempt to maintain; all other agent rules are inactivate until this threshold measure is met

not passionate about the college's success, or even due to some technical aspect of collective routines such as too few brainstorming meetings or a timeline that is impractically short.

Communication norm

The max-align-turn parameter measures the strength of an agent's tendency to align its heading angle with the average heading angle of its peers. It reflects an agent's inclination to follow the coding command "turn towards average-flockmate-heading" (Wilenksy, 1998). The higher the max-align-turn value, the more adept an agent is at aligning its heading angle with the average heading angle of its peers. In some simulated collectives, directional alignment among peers is a strong norm, while in other collectives agents move in different directions. Similarly, in some human collectives, members progress through ways of perceiving and responding to reality in a manner that correlates and aligns with peers, while in other collectives members move through interpretations autonomously. For example, group members have been shown to engage in more open and effective communication in groups with such structural attributes as strong connectedness between members (O'Reilly & Roberts, 1977) and weak faultlines (Lau & Murnighan, 2005). We can say that a group has a strong *communication norm* if its members effectively communicate their interpretations with one another. I define the interaction norm *communication* as the level of an individual's effectiveness at communicating with his/her peers about her interpretations and their interpretations. Individuals are most likely to manifest a strong communication norm when they are high in desire, ability, and opportunity to exchange information and insights with one another. They might engage in the following representative behaviors: voicing thoughts; not self-silencing due to self-doubt or conflict-avoidance; wanting to contribute; speaking and thinking in a lexicon understood by peers; listening to peers; learning from peers; and transferring peer knowledge to the context of one's own work.

The relationship between the max-align-turn command and the communication norm as defined in this study is nuanced and bears further elaboration. The human act of communicating has two distinct components: the act of expressing a communication and the act of receiving a communication. Communication between two people is only as strong as the weakest of these two components. In other words, if we rank communication effectiveness on a scale of 1 to 10, and person A expresses at level 4 while person B receives at level 7, then the communication effectiveness between person A and person B will be at 4. If person A expresses at level 7 and person B receives at level 4, communication effectiveness will also be at level 4. This is relevant because the flocking model's max-align-turn command reflects only the act of receiving a communication; it does not capture communication expression. Agents express information in the flocking model by making movements, and there is no variance in this expressive component between different collectives. All agents in all collectives move, or express, with perfect clarity and effectiveness. Reception is the sole communication component to vary between collectives. Given that overall communication effectiveness is only as strong as the weakest of its component parts, and given that expression is perfect in all collectives, then variance in overall communication effectiveness is adequately captured by variance in communication reception. Therefore, I treat the max-align-turn command in the model as a serviceable proxy for overall communication effectiveness in the model. The model aims to represent overall communication effectiveness in human contexts, and thus the max-align-turn command is suited to this purpose. However, it should be noted that when I transition to discussion of variance in overall communication effectiveness in human contexts, I reference potential variance in both expressive and receptive sub-components.

The faculty in our hypothetical vignette exhibits a strong communication norm if members effectively voice to each other—and hear from each other—their various individual interpretations of what "Global College" means and entails. The faculty has a weak communication norm if professors do not effectively convey and receive ideas on the challenge at hand. Weak communication may result from lack of desire, ability, or opportunity to exchange information and insights. For example, professors may lack desire to communicate because the issue matters too little to them. Or, they may be convinced of the rightness of their own views and consequently have no desire to exchange views with peers. The communication norm is weakened if individuals have such divergent values, assumptions, objectives, methods, and lexicons that they speak past and do not hear one another. Finally, opportunity is critical to effective communication. Just as holding too few brainstorming meetings undermines the uniqueness norm, holding too few meetings to enable faculty discussion of insights and options hamstrings communication efforts.

Consensus norm

The max-cohere-turn parameter measures the strength of an agent's tendency to move its position toward the average position of its peers. It reflects an agent's inclination to follow the coding command "turn towards average-heading-towards-flockmates" (Wilenksy, 1998). To execute this command, the program calculates the heading that the focal agent would have to pursue to move toward each individual peer, then averages these headings to determine the agent's desired heading. In essence, the command moves the focal agent toward the collective's average position. The greater an agent's max-cohere-turn value, the greater its capacity to move toward its peers and the greater its coherence with the flock. In some simulated collectives positional coherence among peers is a strong norm, while in other collectives agents exhibit little inclination to cohere with other agents. Similarly, human collectives differ from one another in the extent to which their members seek to forge shared ways of perceiving and responding to reality (Echterhoff, Higgins, & Levine, 2009), seek consensus and validation (Bechtoldt et al., 2010), and develop shared cognitions (Ensley & Pearce, 2001; Klimoski & Mohammed, 1994). We can say that a group has a strong *consensus norm* if its members are highly inclined to synthesize shared interpretations. I define the interaction norm *consensus* as the strength of an individual's tendency to forge with his/her peers shared interpretations. This definition is consistent with scholarship showing that the need for inclusion, like the need for differentiation, is a fundamental human drive (Brewer, & Pickett, 1999). Just as the max-separate-turn and max-cohere-turn rules pull simultaneously in opposite directions in the flocking model, so the uniqueness norm and the consensus norm pull simultaneously in opposite directions in group contexts. Individuals are most likely to manifest a strong consensus norm when they are high in desire, ability, and opportunity to forge shared ways of perceiving and responding to reality. They modify, amend, adjust, and revise their cognitions and perspectives to more closely resemble those of their peers. This process results in them forging with their peers a degree of commonality in their understandings of what problems exist, what solutions are promising, and how work should be done.

The professors in our running example exhibit a strong consensus norm if they collectively work toward a shared understanding of what “Global College” means and entails. They bring diverse individual opinions about how the new strategic position might be supported by specific decisions on resource allocation, curricular content, and in-class pedagogy. Some departments are enthusiastic about gaining courses and faculty positions as a result of the strategic change; others are concerned about losing courses and clout. Some professors are excited about revising course content and adjusting pedagogy to reflect global issues and dynamics; others are resistant to the loss of autonomy such changes represent. Consensus behaviors include collectively engaging divergent perspectives, working through opposing interests, staying the course through uncertainty and conflict, and naming and enduring loss. Not all collectives are governed by strong consensus norms. A faculty with a weak consensus norm, for example, is comfortable with each department—or even each professor—interpreting “Global College” in his or her own way. A college with a weak consensus norm houses a multitude of divergent understandings of global rather than a shared collective understanding.

Conformity intolerance norm

The minimum-separation parameter indicates the minimum distance of separation that two agents attempt to maintain. The Netlogo flocking algorithm prioritizes the minimum-separation boundary; when minimum-separation is breached, alignment and coherence rules are deactivated until it is restored. Thus, the minimum-separation parameter embodies a more intractable dimension of agent diversity than mere positional and heading variety; it embodies resolute opposition. In some simulated collectives there is a strong norm of maintaining a high minimum level of separation between agents, while in other collectives inter-agent positional proximity is tolerated and the norm is a low minimum level of separation. Similarly, human collectives differ from one another in the extent to which they tolerate conformity in ways of perceiving and responding to reality. We can say that a group has strong *conformity intolerance norm* if its members are highly averse to forging shared interpretations. I define the interaction norm *conformity intolerance* as the strength of an individual's tendency to resist his/her peers' ways of perceiving and responding to reality. Theoretical and empirical grounding for the conformity intolerance construct is provided by Snyder and Fromkin (1980), who cite a string of experiments showing that people push back strongly when their minimum threshold level of need for uniqueness is breached. When made to feel that their attitudes were very similar to those of their peers—when their sense of uniqueness was threatened—research subjects in a variety of scenarios responded by changing their attitudes in order to re-establish a comfortable level of uniqueness (Snyder & Fromkin, 1980). An individual with a strong conformity intolerance norm might exhibit the following representative behaviors and priorities: resisting and silencing peer interpretations without giving them an open hearing and without weighing them against one's own interpretations (whether out of dislike of peers or because peer interpretations represent some sort of loss); prioritizing the uniqueness of one's own interpretations above all else and at the expense of all else; being wedded perpetually to hypotheticals and possibilities only; and being unwilling to commit to a decision.

In the college example, the faculty has a strong conformity intolerance norm if members are highly resistant to forging a shared interpretation of what “Global College” means and entails. This resistance has several potential causes. It may stem from personal and professional rivalries that predate the work at hand but that undermine collective progress on forging a shared interpretation. Alternately, conformity intolerance may reflect collective indecisiveness. The faculty remains stuck in discussions of hypotheticals and possibilities, either because it fears that committing to a course of action opens it up to the possibility of failure, or because it is unable or unwilling to acknowledge and accept the loss that comes with deciding and acting.

Peer exposure norm

The vision parameter indicates the maximum distance that an agent is capable of sensing peers. In simulated collectives, the greater an agent's vision, the more peers with which the agent interacts. Similarly, human collectives differ in the extent to which their members interact with one another. We can say that a group has strong *peer exposure norm* if its members interact with a large number of peers. Several measures reflecting the peer exposure construct have been used in the psychology and organizational literatures, including group connectedness—which O'Reilly and Roberts (1977) compute by dividing the number of direct links among members by the total number of direct links possible—and network centrality—which Liu and Ipe (2010) define as the extent to which the individual is linked to others in the group, and which Oldroyd and Morris (2012) average across members of the collective to capture the extent to which team members are linked to one another. I define the interaction norm *peer exposure* as the extent to which an individual is exposed to the interpretations of other individuals within the collective. An individual with a high level of peer exposure will interact with a large number and a high proportion of peers.

The peer exposure norm is high in the college example if the professors have a high level of exposure to peer understandings of what “Global College” means and entails. A high peer exposure norm is reflected in an appropriate number of information sessions, well-attended faculty meetings, and discussions in which a high proportion of professors play active roles. Conversely, a low peer exposure norm is reflected in infrequent, sparsely-attended meetings that are dominated by a few recurring voices.

Translating the model: collective behaviors

Interaction rules govern individual decisions in flocking simulations. From these many localized decisions, collective behavioral patterns emerge over time. I have thus far proposed five specific behavioral correlates to NetLogo's interaction rules. The remaining step in creating a Flock Leadership model is to establish behavioral analogues to different types of collective behaviors that emerge in NetLogo. Stonedahl and Wilensky (2010) identify three emergent collective behaviors commonly found in flocking simulations: convergence, volatility, and non-convergence. As shown in Table 2, the properties defining these three simulated behaviors correlate, respectively, to three emergent properties of human collectives that I call *technical capacity*, *adaptive capacity*, and *incapacity*.

Technical capacity

Convergence is a collective property reflecting the extent to which agent headings are parallel. It can be measured with an objective function calculating the sum of the square roots of the variances between each agent's heading and the heading of the set of agents; where the objective function is minimized, convergence is greatest. Fig. 1 compares convergent flocks to volatile and non-convergent flocks along the dimension of alignment in agent headings. The results are obtained from simulations conducted in BehaviorSpace, a parameter-sweeping software application integrated into NetLogo. BehaviorSpace simulation data can be analyzed in Excel. I set population at 30 agents to reflect a mid-sized collective that one might find in an organizational unit, but the collective property convergence is not highly sensitive to population size. Even with populations as low as five, convergent flocks quickly manifest alignment in agent heading. I conducted 50 simulations for each flock type to counteract the effect of anomalous runs. Each simulation lasted 500 iterations (model time steps), which were more than enough to capture the emergent collective behaviors of the different flock types. The y-axis of Fig. 1 shows the standard deviation of individual headings at each iteration, in degrees, averaged across the 50 simulations for each flock type. Where standard deviation of individual headings is lower, alignment is higher. Thus, Fig. 1 shows that inter-agent alignment is highest in convergent flocks, somewhat strong in volatile flocks, and non-existent in non-convergent flocks.

Convergence—or alignment in agent headings—should not be confused with close proximity in agent position. In fact, agents in highly convergent flocks maintain some positional distance from one another. Convergent flocks move in relatively straight lines; collective net motion from T_x to T_{x+1} extends—incrementally and predictably—the trajectory established through T_{x-1}, T_{x-2}, T_{x-3}, and so forth backward in time. Fig. 2 contains screenshots of convergent, volatile, and non-convergent flocks:

Simulated collectives differ from one another in the extent to which agent headings are parallel and collective net movement occurs in straight and predictable trajectories. Similarly, human groups differ from one another in the extent to which individual interpretive headings align and in the degree to which collective interpretive movement extends the existing track record. I define *technical capacity* as collective learning that incrementally extends and refines existing ways of perceiving and responding to reality. Organizational learning draws on both exploitation of current knowledge and exploration of new knowledge (Andriopoulos & Lewis, 2009; Jansen, Van Den Bosch, & Volberda, 2006.). Established in the literature over two decades ago by March (1991), the essential tension between exploitative and exploratory learning remains central to innovation research (Gupta, Smith, & Shalley, 2006). Technical capacity reflects exploitative learning, or "the refinement and extension of existing competencies, technologies, and paradigms" (March, 1991, p. 85). Like exploitative innovation, technical capacity requires efficiency and convergent thinking (Wadhwa & Kotha, 2006) and serves to "broaden existing knowledge and skills, improve established designs, expand existing products and services, and increase the efficiency of existing distribution channels" (Jansen et al., 2006).

Technical capacity reflects the collective refinement, extension, broadening, and improvement of existing interpretive positions, defined as bundles of cognitions and perspectives comprising individuals' ways of perceiving and responding to reality. Individual members of a group high in technical capacity may occupy distinct interpretive *positions*; their ways of perceiving and responding to reality are not identical. At the same time, a group high in technical capacity consists of individuals with interpretive *headings* that are highly aligned, coordinated, complementary, oriented toward the same purpose, and that extend the trajectory of past interpretive progress.

Adaptive capacity

Volatility is a collective property reflecting the extent to which global flock heading changes. A flock is volatile when it exhibits nonlinear, unpredictable net movement. Volatility can be calculated by adding together the standard deviation of mean flock headings along the *y* dimension through all previous iterations (or through the previous 100 iterations if there are more than

Table 2.
Collective capacities and associated model variables.

Collective capacities	Associated model collective behaviors
Technical capacity: collective learning that incrementally extends and refines existing ways of perceiving and responding to reality	Convergence: collective behavior in which agent headings are highly aligned, agent positions are spaced apart, and collective net movement follows a linear path
Adaptive capacity: collective learning that transforms or replaces existing ways of perceiving and responding to reality	Volatility: collective behavior in which agent headings are moderately highly aligned, agent positions are tightly packed, and collective movement follows a nonlinear trajectory that continually changes
Incapacity: the absence of collective learning	Non-convergence: collective behavior in which agent headings are highly unaligned, agent positions are spaced apart, and no collective net movement occurs

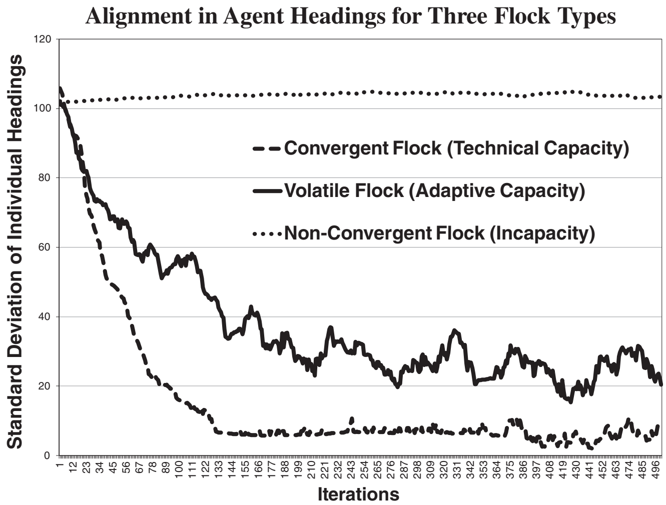

Fig. 1. Alignment in agent headings for three flock types.

100 in total) and the standard deviation of mean flock headings along the *x* dimension through the same number of iterations. A volatile flock's future movements bear little relation to its movement history; mean headings at T_{x-3}, T_{x-2}, T_{x-1}, and T_x are poor indicators of mean headings at T_{x+1}. Fig. 3 compares volatile flocks to convergent and non-convergent flocks along the dimension change in flock heading. This measure is assessed and averaged across 50 simulations for each flock type, at each iteration, with each simulation lasting 500 iterations, and agent population set at 30, as was the case with the analysis of convergence. Fig. 3 illustrates the wide behavioral gulf between the predictable collective movement associated with technical capacity and the continually changing, novel collective direction associated with adaptive capacity.

Just as simulated flocks differ from one another in the extent to which their headings are nonlinear and unpredictable, human groups differ in the extent to which their collective interpretive trajectories change courses and take unexpected turns into novel territory. I define *adaptive capacity* as collective learning that fundamentally transforms or replaces existing ways of perceiving and responding to reality. Adaptive flocks are proficient at the process of discovery. The volatile trajectories they pursue through interpretative space represent engagement with substantially novel cognitions and perspectives. Adaptive capacity reflects exploratory learning in that it involves "experimentation with new alternatives" (March, 1991, p. 85) and yields such outcomes as fundamentally new designs, new production processes, new markets, or new channels of distribution (Abernathy & Clark, 1985; Jansen et al., 2006).

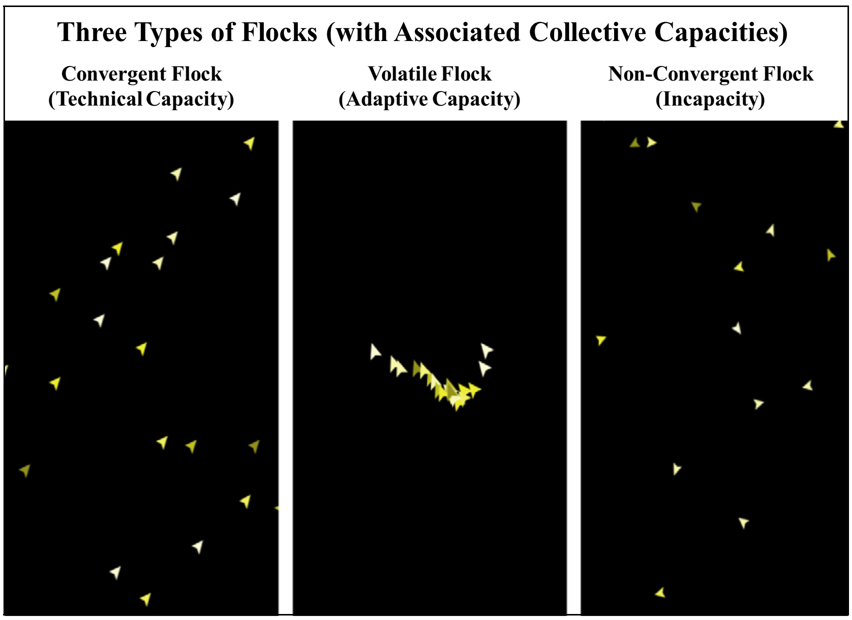

Fig. 2. Three types of flocks (with associated collective capacities).

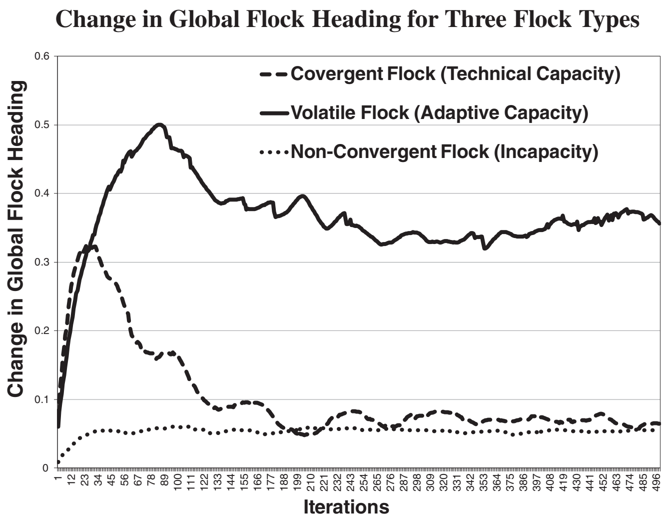

Fig. 3. Change in global flock heading for three flock types.

Incapacity

Non-convergence is a collective property reflecting the extent to which agents head in different directions at different angles. Like convergence, non-convergence can be measured by calculating the sum of the square roots of the variances between each agent's heading and the heading of the set of agents. Whereas convergence is greatest where the objective function is minimized, non-convergence is greatest where the objective function is maximized. While individuals within a non-convergent collective change their positions over time, the collective as a whole experiences little-to-no net movement because agent headings offset one another. Thus, non-convergent collective behavior resembles a static, cloud-like swarm rather than a moving flock. Similarly, some human groups occupy the same interpretive space over time without moving. I define collective *incapacity* as the absence of collective learning. Members of a group high in incapacity maintain distinct interpretive positions *and* divergent interpretive headings, indicating the absence of any common objective or orienting principle. The absence of collective learning is not something that a flock leader would likely want to cultivate. Incapacity is included in this study merely as a baseline against which to compare technical and adaptive capacity, not as an aspirant property.

Phenomena-based modeling results

I have proposed five individual-level and three collective-level behavioral correlates to simulated behaviors found in NetLogo's flocking model. A framework has thus been established for conducting simulations and analyzing relationships between individual- and collective-level processes. I now conduct phenomena-based—or backward—modeling, which aims to deduce patterns of interaction underlying *a priori* specifications of systems behavior (Resnick & Wilensky, 1998). In the terminology of NetLogo's flocking model, the phenomena-based modeling approach asks, “What configurations of individual-level parameter settings are best suited to generating convergent and volatile collective behaviors?” Translated into the language of Flock Leadership, our question reads, “What configurations of uniqueness, communication, consensus, conformity intolerance, and peer exposure norms are best suited to generating technical capacity and adaptive capacity?”

Analyzing how model parameters influence collective behavior in agent-based models poses unique challenges. The large number of parameters and possible values for each parameter mean that parameter space can consist of a great many permutations. In the flocking model, the max-separate-turn, max-align-turn, and max-cohere-turn parameters each have 81 possible values, the vision parameter has 41 possible values, and the minimum-separation parameter has 21 possible values. Thus, parameters space in the flocking model consists of $81 \times 81 \times 81 \times 41 \times 21 = 457{,}570{,}701$ possible permutations. Furthermore, because agent-based models are typically stochastic, multiple trials are necessary to evaluate their behavior. For these reasons, analysis by full factorial experimental design is not feasible (Stonedahl, 2011). The best way to analyze agent-based models of complex systems, argue Stonedahl and Wilensky (2010), is to design objective functions that frame model exploration as search problems. Stonedahl (2010) accomplishes this in BehaviorSearch, a NetLogo-compatible software program that searches model parameter space, generates data, employs a specified measure of collective behavior, and subjects the measured data to an objective function. The purpose of BehaviorSearch is to identify interaction rule parameter values most likely to yield specified collective behaviors.

BehaviorSearch enables users to select from four search algorithms: random search, mutation hill climber, simulated annealing, and standard genetic algorithm. Random search is a naïve baseline method that randomly generates one set of parameters after another, computes the objective function for each, and at the conclusion of the search simply returns the best set of mutations it finds. Mutation hill climber starts with a random location in parameter space, repeatedly generates a neighboring location, and then moves to the new location if it is better than the old location. Simulated annealing operates much like mutation hill climber, except that an inferior move is also possible based upon a probability value that changes over time (Stonedahl, 2010). The standard genetic algorithm employs an iterative search process in which candidates—sets of parameter values in the case of the flocking model—are evaluated against the objective function, the fittest candidates are chosen, and their properties are modified to create the next generation of candidates. For a number of reasons, the standard genetic algorithm is the best choice for searching parameter space in the flocking model. First, genetic algorithms are capable of searching multiple regions of parameter space simultaneously (Stonedahl & Wilensky, 2010), which enables them to avoid getting trapped in local optima (Stonedahl, 2011). Second, genetic algorithms have an established history of being used to solve search problems. They were employed nearly half a century ago to optimize the parameters for a simulated living cell (Weinberg, 1970), and they have since been applied frequently to parameter optimization problems in agent-based models (e.g., Back & Schwefel, 1993; Grefenstette, 1986; Stonedahl & Rand, 2007). Finally, Stonedahl and Wilensky's (2010) work comparing random search, mutation hill climber, and genetic algorithm search methods in flocking models specifically demonstrates that the genetic algorithm is vastly superior to random search and marginally more efficient than the mutation hill climber. For these reasons, I used genetic algorithms to search for optimized parameters underlying technical capacity, adaptive capacity, and incapacity.

My choices of genetic algorithm search specifications were informed as well by Stonedahl and Wilensky (2010), who have researched the comparative efficiency of different search specification values for genetic algorithms when the latter are used to explore flocking models. Genetic algorithm search specifications were as follows: population-size (the number of sets of parameter values in each generation, where each set consists of a value for uniqueness [max-separate-turn], a value for communication [max-align-turn], a value for consensus [max-cohere-turn], a value for peer exposure [vision], and a value for conformity [minimum-separation]) 30; crossover-rate (the probability of using two existing sets of parameter value when creating a next-generation set of parameter values; crossover-rate reflects the extent to which the genetic algorithm converges on a specific solution) 0.7; mutation-rate (the probability of a *random* jump to a new set of parameter values occurring; mutation-rate reflects the extent to which the genetic algorithm explores new parameter space) 0.05; and tournament-size (the number of sets of parameter values that compete to be selected for reproduction) 3. Fixed sampling was set at 5, meaning the objective function was averaged across five model runs with different random seeds, to reduce variability arising from model stochasticity (Stonedahl & Wilensky, 2010). Measures were collected after 75 iterations, which were sufficient to reveal when a set of parameters was or was not generating convergence, volatility, or non-convergence, and search algorithms were stopped after the model had been run 12,000 times. To ensure that search findings were not anomalous, each was repeated numerous times. The searches for technical capacity and collective incapacity were repeated 30 times each, and the search for adaptive capacity was repeated 60 times to improve statistical confidence (Stonedahl & Wilensky, 2010). Search space specifications were as follows: max-separate-turn, max-align-turn, and max-cohere-turn, 0, 0.25, 20 (meaning the parameters ranged from 0 to 20, by increments of 0.25); vision 0, 0.25, 10; and minimum-separation 0, 0.25, 5. These parameter ranges and increments are the same as appear in the NetLogo flocking model itself. Results are reported below.

Norm configuration underlying technical capacity

Technical capacity is collective learning that incrementally extends and refines existing interpretations. Fig. 4 shows that technical capacity is most robust in groups where the uniqueness norm is moderately high, communication and peer exposure norms are very high, and consensus and conformity intolerance norms are very low. These phenomena-based modeling results should be interpreted qualitatively. For example, the uniqueness norm should be viewed as “moderately strong”; were it 9.5 out of 20 or 10 out of 20 rather than 9 out of 20, this qualitative understanding of the results would not be materially different.

This norm configuration informs several inferences about the interaction dynamics underlying technical capacity. The moderately strong uniqueness norm promotes a variety of interpretations within the collective. The high communication norm permits

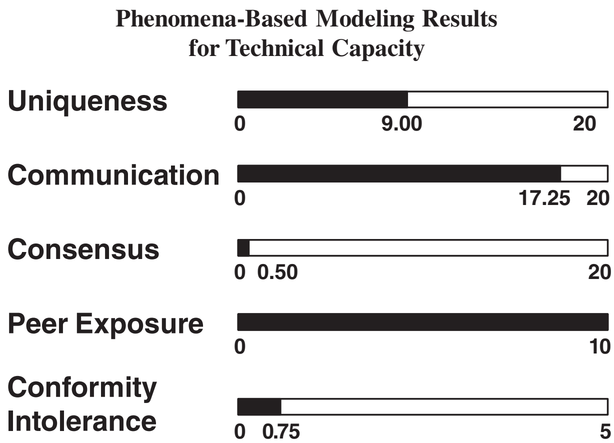

Fig. 4. Phenomena-based modeling results for technical capacity.

communication effectiveness and the high peer exposure norm means that group members interact with a large number of individuals. Together, the high communication and peer exposure norms mean that flock members are exposed to many peer interpretations. The very low conformity intolerance norm means that group members are not highly resistant to peer's ways of perceiving and responding to reality. Finally, the very low consensus norm disinclines individuals from synthesizing with their peers shared interpretations. In other words, diversity is generated and flock members are exposed to many diverse interpretations, and the interpretive diversity is not reduced through a consensus-forging process of conflict, loss, and choice. Variety in interpretive positions persists. Individuals are exposed to the cognitions and perspectives of their peers, but they do not work toward developing with their peers shared cognitions and perspectives. Individuals *are* influenced by their peer's interpretive *headings*. An individual's trajectory is influenced by its peers' trajectories; each individual moves through different patches—representing different cognitions and perspectives—but in the same direction. This collective behavior can be interpreted as a type of division of labor enabled by the low consensus norm. Individuals cooperate toward a common purpose but specialize in the performance of different roles and tasks.

Revisiting the hypothetical college example, the faculty is high in technical capacity if it demonstrates collective learning that incrementally extends and refines existing interpretations of the “Global College” strategy. Professors draw on past experiences, disciplinary perspectives, observed competitor behavior, and researched “best practices” to inform their endorsements of various curricular and co-curricular initiatives. They fit the programming they endorse to the context of their specific institution, but they do not generate appreciably novel interpretations of “Global College” so much as they modify, amend, extend, deconstruct and recombine, refine, and enhance existing conceptualizations and enactments from a variety of sources. Faculty members' interpretive headings are aligned and parallel, meaning that their efforts are oriented in the same direction. At the same time, their interpretive positions are not identical. Different departments and individuals develop and maintain distinct understandings and enactments of what “Global College” means and entails. For example, an economics professor's way of perceiving and responding to this challenge is informed by his/her experiences, disciplinary perspective, and research on best practices. The economics professor listens as a philosophy professor—expressing a portion of his/her own interpretative position informed by his/her own experiences and biases—advocates a specific pedagogy such as holding weekly joint seminars via video conferencing with a philosophy class in another country. In a technical flock, the economics professor listens to this idea, but adopts only such elements of it as translate to the context of his/her work. In other words, the economics professor interprets and enacts the pedagogy in a way that informs his/her own work trajectory. The very low consensus norm means that conflict is not collectively engaged to forge a *shared* interpretation of this specific pedagogy.

Norm configuration underlying adaptive capacity

Adaptive capacity is collective learning that fundamentally transforms or replaces existing interpretations. Fig. 5 shows that adaptive capacity is most robust in groups where uniqueness and consensus norms are moderately high, communication and peer exposure norms are very high, and the conformity intolerance norm is very low. The main difference between the behavioral norm configuration underlying technical capacity and that underlying adaptive capacity is that the consensus norm is substantially higher in adaptive flocks than in technical flocks. As with technical flocks, the strong uniqueness norm in adaptive flocks enables the generation of a variety of interpretations while the high communication and peer exposure norms facilitate the sharing of interpretations throughout the collective. In contrast to technical flocks, however, the interpretive diversity that is generated and communicated in adaptive flocks does not persist; rather, it is reduced through consensus-making processes of conflict, loss, and choice. The moderately high consensus norm in adaptive flocks inclines individuals to forge with their peers shared interpretations. Individuals have a tendency to modify and amend their own cognitions and perspectives such that they

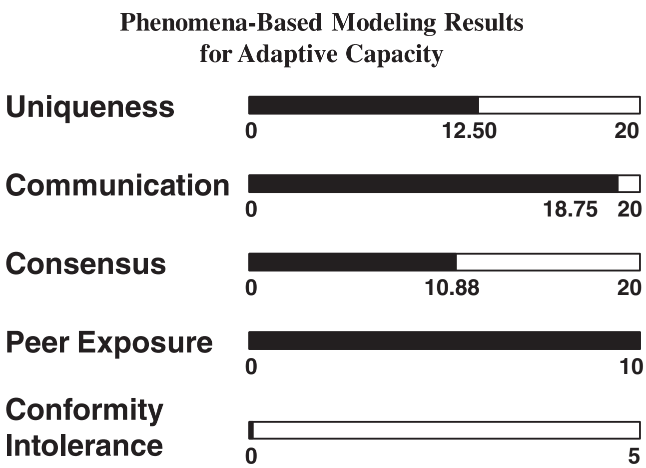

Fig. 5. Phenomena-based modeling results for adaptive capacity.

more closely resemble those of their peers. They are inclined to embrace peer insights and to develop common understandings of what problems exist, what solutions are promising, and how work should be done. At the same time, the moderately strong uniqueness norm remains. Thus, there is an ongoing, irresolvable, oppositional volatility infusing adaptive capacity. The tension between diversity generation and consensus formation—between the inclination to think uniquely and the inclination to find agreement, to avoid the crowd and to join the crowd—is the wellspring of adaptive capacity's transformative energy. This tension fuels the ferment associated with inspiration, discovery, and transformation.

The faculty in the hypothetical college example is high in adaptive capacity if it demonstrates collective learning that fundamentally transforms or replaces existing interpretations of the "Global College" strategy. As is the case with the faculty high in technical capacity, professors communicate their support for various curricular and co-curricular initiatives based upon their professional experiences and disciplinary perspectives. The faculty high in adaptive capacity, however, is distinct in that its members engage the process of forging shared interpretations. For example, several professors advocate a definition of "global" that deemphasizes geography and stresses instead the networked interconnectivity of the human experience, and seek to curricularly enact this interpretation with team-taught, problem-based inter-disciplinary courses. In an adaptive faculty, the factions that endorse, that oppose, and that remain undecided about this proposal all enter into a process of working toward a shared interpretation. This collective work entails raising questions, surfacing hidden assumptions, noting weaknesses, suggesting improvements, identifying opportunities unique to this institution's environment, naming losses associated with the proposal, and acknowledging the painful reality for individuals and factions bearing those losses. It is important to note that while adaptive collectives are inclined to work toward shared interpretations, this does not mean that every individual and faction will be pleased with every outcome. The consensus norm is a norm only, and it should not be confused with uniform agreement. Indeed, the process of working toward consensus may surface conflict. But just as the join-avoid, consensus-diversity tension heightened during the process of working toward shared interpretations generates conflict, it produces as well the creative, transformative solutions associated with adaptive capacity.

Norm configuration underlying incapacity

Collective incapacity is the absence of collective learning. Fig. 6 shows that incapacity is most robust in groups where uniqueness, communication, and peer exposure norms are relatively low, the consensus norm is moderately high, and the conformity intolerance norm is very high. Flocks high in incapacity are distinct from both technical and adaptive flocks in that the former have substantially lower peer exposure, communication, and uniqueness norms and substantially higher conformity intolerance norms. Little interpretive diversity is generated, and what is generated is not amplified and diffused because individuals do not interact with a large number of peers, they are ineffective at communicating with peers with whom they do interact, and they are strongly inclined to resist those interpretations with which they come in contact. As previously noted, collective incapacity represents a baseline against which to compare technical and adaptive capacity, not an aspirant property.

Discussion

This study has elucidated a model and specific constructs at the individual and collective levels of analysis that conceptualize and categorize human activities within a framework of emergence. Phenomena-based modeling has identified distinct interaction norm configurations underlying three collective capacities. The theoretical model, component constructs, and simulation analyses developed in this study establish the foundation for a Flock Leadership research agenda. Two core takeaways are that leadership in complex contexts is about understanding and influencing systems interactions—not about directing followers—and that we can

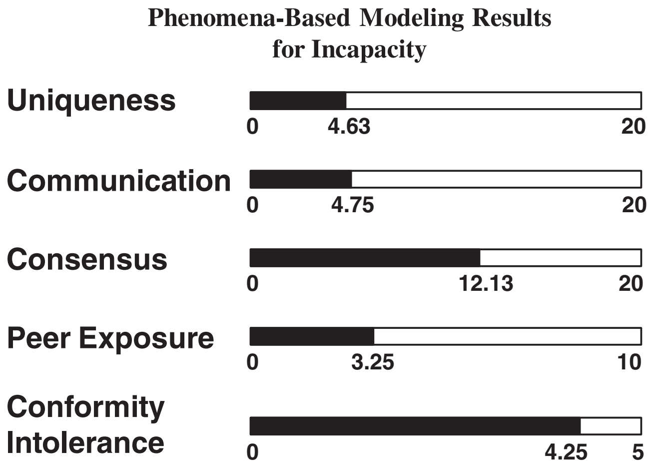

Fig. 6. Phenomena-based modeling results for incapacity.

model those interactions and link them to collective capabilities with sufficient specificity to inform and assist those exercising leadership. From these central takeaways derive several related implications for leadership theory, research, and practice.

Implications for theory

Flock Leadership has important implications for how leadership is theorized. One exercises Flock Leadership by first assessing the essential nature of the challenge (i.e., technical or adaptive) confronting the group, and then promoting the norm configuration from which the collective capacity needed to engage that challenge is most likely to emerge. Thus, the Flock Leadership framework spotlights two elements of the leadership equation: the nature of the challenge itself, and the interaction norms governing how group members relate to one another. These distinctive points of emphasis establish for Flock Leadership a unique theoretical position. It is a type of contingency theory, but it does not speak to the contextual appropriateness of specific leadership behaviors or styles as do previous contingency theories (e.g., Fiedler, 1964; Hershey & Blanchard, 1969; Kerr, Schreisheim, Murphy, & Stogdill, 1974). It is focused on problem-solving, but it does not position the leader as problem-solver. It is, uniquely, a contingency theory of emergent collective capacity.

The standard approach of contingency theories of leadership has been to ask what leadership styles and behaviors are appropriate to a given context, where context consists of such elements as leader position power, leader–member relations, and characteristics of the task, organization, or subordinates (Fiedler, 1964; Kerr et al., 1974). Flock Leadership is a contingency theory in the sense that it first asks what the group intends to accomplish. In contrast to previous contingency theories, however, Flock Leadership does not seek to match leadership styles and behaviors to different contingencies. It is not a theory about leadership styles and behaviors at all; rather, it is a theory about group capacity development. Flock leadership views group capacity not as something directed, motivated, persuaded, or inspired directly by a leader, but rather as the emergent consequence of interactions between group members. Norm configuration, not leadership style, is the key driver of collective capacity. Appropriate leadership styles, behaviors, and tactics are those that promote the norms best suited to generating the collective capacity desired.

Viewing collective capacity as an emergent phenomenon fundamentally reframes the aims and responsibilities of leadership. The following description of the functional model of leadership is a representative articulation of conventional expectations that leaders decide, orchestrate and implement: "leaders are responsible for (a) diagnosing any problems that could potentially impede group and organizational goal-attainment, (b) generating and planning appropriate solutions, and (c) implementing solutions within typically complex social domains" (Zaccaro, Rittman, & Marks, 2001, p. 454). In this view, leaders are charged with generating and implementing the right solutions. Flock Leadership takes a more limited view of the capacity of leaders to know best. Indeed, it represents a fundamentally different perspective on what is knowable. In the Flock Leadership framework, the general properties of technical and adaptive capacities are knowable, but the specific interpretations that will arise from those capacities are *a priori* unknown. It is not the responsibility of a flock leader to generate and implement specific solutions; it is her responsibility to build *the collective's* capacity for enacting those behaviors. The leader who herself determines solutions and motivates or directs the group to implement them suppresses all potential solutions that might have emerged had she cultivated generative interaction norms. The purpose of flock leadership is not to direct the collective toward a particular answer, but rather to promote conditions that generate either predictable, incremental learning or unpredictable, transformative learning. A Flock Leader encourages either the *emergent enhancement* of existing cognitions, perspectives, beliefs, habits, and priorities, or the *emergent creation* of ones that do not currently exist.

Implications for research

This study paves the way for future research along several paths. First, the framework developed here might be applied to leadership challenges in a variety of contexts. Second, the foundation established in this study creates an opportunity for exploratory simulation modeling aimed at identifying critical points and enhancing our understanding of nonlinearity in processes of human organizing. Finally, this study sets the stage for empirical work testing the relationships proposed here. I will discuss each of these research implications in turn.

The Flock Leadership framework can be applied to a range of contexts in which human collective efforts are interconnected but not centrally orchestrated. The approach introduced in this study—translating constructs reflecting human activity at the individual and collective levels of analysis into flocking model algorithms and movement patterns—might be brought to such varied concerns as organizational ethics, organizational culture, team creativity, and industry evolution. Treating these dynamics as types of emergent collective behavior will generate an abundance of fresh questions and insights. In the case of ethics, for example, both personal ethics and organizational ethics have been analyzed extensively, but the relationship between the two remains theoretically underdeveloped. Framing organizational ethical capacity as emergent collective capacity spawns interesting questions that flock modeling can help explore. How do norms shaping individual-level ethical interpretations and interactions influence emergent collective ethical capacity? Are particular types of organizational ethical capacity best suited to particular types of ethical challenges, and if so, what can organizational leaders do to promote the right type of ethical capacity for the organization's environment? The Flock Leadership framework might inform similar research questions in the areas of organizational culture and team creativity. Flocking modeling might be employed, as well, at a broader level of analysis such that agents represent firms and collective behavior represents industry dynamics. In this context, the analytical focus would be on identifying different patterns of firm-firm interaction underlying different forms of industry-level outcomes, such as radically innovative collective behavior versus incrementally innovative collective behavior.

A second research path for which this study sets the stage is exploratory simulation modeling, which is a methodology for analyzing the robustness of a collective state. Exploratory (or forward) modeling is essentially the inverse of phenomena-base modeling. The latter identifies interaction norm configurations associated with pre-specified collective behaviors; the former examines collective properties generated when simulations are run with pre-specified interaction norms. Exploratory modeling identifies critical points where collective behaviors are highly sensitive to even slight changes in individual behaviors. For example, exploratory modeling can analyze how increasing the consensus norm affects change in global flock heading in a technical flock, or how decreasing the uniqueness norms affects alignment in agent headings in an adaptive flock. Steadily increasing the consensus norm may affect change in global flock heading in a technical flock very little, and then a subsequent small change in consensus may greatly impact change in global flock heading. The consensus norm value at which collective behavior becomes very sensitive and fragile is called a critical point.

Future simulation research mapping the critical points and nonlinearities associated with technical and adaptive capacity promises to have important implications for how leadership opportunities and dangers are theorized. The organizational literature approaches exploitative and exploratory learning as dichotomous collective outcomes that are either spatially or temporally compartmentalized. The *ambidexterity* approach compartmentalizes the dichotomy spatially; it entails separating exploitation and exploration into different organizational subunits that are only weakly integrated with each other (Benner & Tushman, 2003). The *punctuated equilibrium* approach compartmentalizes the dichotomy temporally; it involves sequential allocation of attention and resources to the divergent orientations, with bursts of exploration punctuating extended periods of exploitation (Burgelman, 2002; Tushman & Romanelli, 1985). Flock Leadership conceptualizes collective capacities as emergent outcomes of systems of interactions. If future exploratory modeling shows that deep nonlinearities characterize these systems at critical points, it may be less useful to conceptualize incremental and transformative learning as compartmentalized outcomes than it will be to view them as different processes comprising a duality of learning.

If future exploratory modeling informs researchers and leaders how to leverage influence at critical points, they may find that transitions between technical and adaptive capacity are more readily achieved than previously theorized. This study's phenomena-based modeling results suggest that the key to transitioning between technical and adaptive capacity is flexibility in a collective's consensus norm; exploratory modeling will help specify the level of consensus at which systems are particularly amenable to change. Knowledge of these relationships may enable leaders to cultivate adaptive capacity during idea generation and experimentation stages of engaging a challenge, then reduce consensus practices and behaviors in order to shift the collective toward technical capacity when implementation is required. Approaching technical and adaptive capacity as a duality of learning thus opens leadership opportunities, but the existence of critical points implies leadership dangers as well. Sensitive points in any of the five interaction norms may attenuate the boundaries between technical or adaptive capacity on the one hand and incapacity on the other. A full mapping of critical points will help alert leaders to the fragility of boundaries between technical capacity, adaptive capacity, and incapacity.

A third research path that might issue from this study is empirical work testing the relationships proposed here. This will entail operationalizing the interaction norms uniqueness, communication, consensus, peer exposure, and conformity intolerance, as well as the collective constructs technical capacity, adaptive capacity, and incapacity. Empirical measurement of these constructs will move researchers beyond a qualitative understanding of norm configurations, and will enable them to quantitatively test the core findings of this study's phenomena-based modeling. Does evidence support the finding that technical capacity is most robust where consensus and conformity intolerance are low, uniqueness is moderate, and communication and peer exposure are high? Does evidence support the finding that adaptive capacity is most robust where conformity intolerance is low, consensus and uniqueness are moderate, and communication and peer exposure are high? In developing measures of this study's constructs, researchers might use as a starting point established measures of similar constructs in the organizational literature. For example, the construct uniqueness shares key similarities with Harrison and Klein's (2007: 1202) *variety* dimension of team diversity, which reflects the extent to which team members possess "differences in kind, source, or category of relevant knowledge or expertise"; communication has much in common with O'Reilly and Roberts' (1977) *information accuracy* variable; consensus is similar to *shared team mental models*, defined by DeChurch and Mesmer-Magnus (2010, p. 2) as "knowledge structures held by members of a team that enable them to form accurate explanations and expectations for the task, and in turn, to coordinate their actions and adapt their behavior to demands of the task and other team members"; peer exposure is comparable to *network centrality*, which Liu and Ipe (2010, p. 243) define as "the extent to which the individual is linked to others in the group"; and conformity intolerance resembles the *separation* dimension of team diversity, defined by Harrison and Klein (2007, pp. 1202–1203) as synonymous with "disagreement", and as reflective of the extent to which "team members hold opposing positions on a task- or team-relevant issue". At the collective level, technical capacity is similar to *exploitative innovation*, operationalized by Jansen et al. (2006, p. 1666) with a six-item measure capturing the extent to which organizational units "depart from existing knowledge and pursue innovations for emerging customers or markets." Adaptive capacity is comparable to *exploratory innovation*, measured by the same authors with an instrument capturing the extent to which organizational units "build on existing knowledge and meet the needs of existing customers" (Jansen et al., 2006, p. 1666). While these established measures in the organizational literature provide useful starting points for approaching the constructs developed in this study, empirical research into Flock leadership will need to develop new measures that connect the construct definitions to the specific contexts under investigation.

Implications for practice

Exercising Flock Leadership is about influencing interaction norms with an eye toward generating a particular collective capacity. Phenomena-based modeling suggests that moving a collective from incapacity to adaptive capacity entails increasing uniqueness, communication, and peer exposure norms while decreasing the conformity intolerance norm. Moving from incapacity to technical capacity involves the same norm shifts as well as a decrease in the consensus norm. Consensus norm strength is the primary lever for transitions between technical and adaptive capacity. How, then, does one go about influencing uniqueness, communication, consensus, peer exposure, and conformity intolerance norms? These are big questions, and space limitations preclude extensive treatment of the voluminous organizational behavior and human resource management insights that might be invoked to assist leadership practitioners. However, one specific body of thought that specifies systems influence tactics and therefore may be of particular value to individuals exercising Flock Leadership is the Adaptive Leadership framework authored by Heifetz and Linsky (Heifetz et al., 2009; Heifetz & Linsky, 2002; Parks, 2005).

Like Flock Leadership, Adaptive Leadership views leadership as systems influence, but the latter focuses on specific influence tactics for practitioner use. Adaptive Leadership might be invoked to examine with descriptive depth and texture Flock Leadership's implications for practice. For example, Adaptive Leadership specifies means of generating interpretive diversity—represented in Flock Leadership by uniqueness—through such group norms as expecting independent judgment, naming elephants in the room, breaking a large group into subgroups, noticing how factions play into which alternatives get accepted and which get rejected, accepting mistakes, and generating numerous alternative interpretations. Similarly, Adaptive Leadership specifies means of diffusing interpretive diversity—represented in Flock Leadership by communication and peer exposure—through such group norms as leveraging unusual networks within and outside the organization, establishing orienting principles, and having authority figures withhold input to create space for collective voice. Finally, Adaptive Leadership specifies means of promoting interpretive consensus through such group norms as surfacing conflict, tolerating discomfort, sharing a common purpose, engaging in reflection and continuous learning, and not resorting quickly to default interpretations. Applying the brakes to consensus-forging behaviors—or "lowering the temperature," in the terminology of Adaptive Leadership (Heifetz et al., 2009, p. 160)—can be accomplished by employing such influence tactics as focusing on aspects of the problem that have obvious solutions, taking a break, telling a joke, or providing structure by breaking the problem into parts and creating time frames, decision rules, and role assignments. (Heifetz et al., 2009; Heifetz & Linsky, 2002).

Limitations

This study proposes a novel framework for theorizing and analyzing leadership, but it has certain limitations. As is the case in all forms of agent-based modeling, external validity is a concern in flock modeling. Agent-based models simplify in order to focus on core aspects of the phenomena being explored, but in doing so they risk failing to capture critical aspects of reality (Davis et al., 2007). This study's model contains three simplifying rules that carry noteworthy limitations. First, agents in the flocking model are homogeneous, but humans are heterogeneous. Simulated agents base their decisions on interaction rules set at identical parameter values. While group norms in human contexts often incline individuals toward a degree of homogeneity in preferences, expectations, and behaviors, no group of people share fully identical decision triggers as do simulated flock members. Second, the strength of interaction rules in the flocking model are set by the modeler and remain fixed throughout the many iterations of that simulation, but group norms in human contexts are continuously subject to ongoing processes of production and reproduction (Lichtenstein, 2014; Sawyer, 2005). In the flocking model, in other words, agent-agent interactions generate emergent structures, but the model does not allow for those emergent structures to recursively influence agent-agent interaction norms as they do within groups of people (Giddens, 1984). Third, as previously discussed, the max-align-turn command in the flocking model reflects the act of receiving but not the act of expressing a communication. The communication norm that the max-align-turn command represents, on the other hand, involves both communication expression and communication reception. While I treat the max-align-turn command as a serviceable proxy for overall communication effectiveness for the reasons previously elaborated, the technical distinction between the model parameter and the human norm that it represents remains a limitation of the study.

Conclusion

Flock Leadership is predicated on the idea that the collective has greater potential capacity than does the individual leader. Thus, Flock Leadership is not about directing the flock; rather, it is about helping the flock develop its capacity to engage challenges. Different collective capacities are appropriate for different challenges. In contexts such as Herbert von Karajan's Berlin Philharmonic, what is desired is predictable, aligned collective behavior that extends and refines existing organizational strengths. In the face of challenges more closely resembling those confronting Pixar Animation Studios, organizational success depends upon developing and tapping collective capacity to discover substantially new products, services, technologies, markets, cultures, or strategies. Flock Leadership provides a framework for understanding and influencing the emergence of different collective capabilities. It represents a novel way of conceptualizing and modeling interactive dynamics in complex systems, and of linking distinct collective behaviors to specific norm compositions. This study has undertaken the critical first step of introducing the model and explicating core constructs. Looking forward, this work might serve as the foundation of a Flock Leadership research agenda that further refines our understanding of leadership opportunities in the context of organizational emergence.

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