MAIN ARTICLE

Combining stock-and-flow, agent-based, and social network methods to model team performance

Edward G. Anderson Jr,[a]* Kyle Lewis[b] and Gorkem Turgut Ozer[c]

Abstract

Across disciplines, there has been an increasing interest in combining different simulation methods. Team science provides a particularly challenging context because of the interplay across levels of analysis. For example, team performance is decisively influenced by accumulated individual attributes, the interactions among individuals and emergent team structures—each of which is affected by multiple feedback loops at different levels of analysis. To address these challenges, we compare the modeling methods of stock-and-flow models, agent-based models and social network analysis to argue for the advantages of a hybrid approach to formal mathematical modeling in a team science context. We develop a proof-of-concept model, which combines aspects of all three methods, to investigate the effects of expertise, the patterns of members' interactions and diversity-based subgroups on team performance. Novel, important insights into team science theory result from this investigation, including, among others, the dynamic tradeoff between diversity and homogeneity on teams' performance and the importance of the communication network structure in affecting that tradeoff.

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Introduction

Over the past decade, researchers have made great strides in understanding how teams behave, learn and interact using empirical and experimental studies. However, many challenges remain in understanding how the complex dynamic nature of teamwork affects team performance outcomes. For example, explaining how relationships among team members emerge and evolve, and how the structure of those relationships affects team performance over time (and vice versa), could benefit from formal mathematical modeling. Researchers have examined these or related questions one at a time, but they are rarely examined in concert, owing perhaps to the complex interdependent nature of these factors and the difficulty of analyzing these

[a] McCombs School of Business, University of Texas, 1 University Station B6500, Austin, TX 78733, U.S.A.
[b] Technology Management Program, College of Engineering, 1318 Phelps Hall, University of California, Santa Barbara, CA, 93106-5129, U.S.A.
[c] Robert H. Smith School of Business, University of Maryland, College Park, MD 20742, U.S.A.
* Correspondence to: Edward G. Anderson, McCombs School of Business, University of Texas, 1 University Station B6500, Austin, TX 78733, U.S.A. E-mail: edward.anderson@mccombs.utexas.edu
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interdependencies using traditional analytical techniques (Kozlowski *et al.*, 2016). We suggest that one fruitful approach to understanding the dynamic nature of teamwork is to combine known methods in an integrated way. We explore how three modeling methods—stock-and-flow modeling (SFM),[1] agent-based modeling (ABM) and social network analysis (SNA)—can be integrated to examine the complex nature of teamwork. We agree with the conventional truism that any model, with enough manipulation, can replicate any other, no matter what method is used to specify the model. We argue, however, that a hybrid modeling approach combining all three methods can capture synergies that will benefit researchers studying the dynamic evolution of team behavior and outcomes by creating more elegant models that facilitate theory development.

We emphasize team science because it concerns the study of complex interrelationships at multiple levels of analysis: individuals, between individuals (dyads) and the team collective. Despite decades of team science research, many unanswered questions remain regarding how individuals' knowledge is discussed, combined, interpreted and applied to produce team-level learning and performance outcomes in a dynamic context. Recent calls have urged researchers to consider the dynamics inherent to team processes. For example, Cronin *et al.* (2011) argue that critical insights about team science have been masked by an overemphasis on static measures and cross-sectional research designs. Kozlowski *et al.* (2016) suggest that computational modeling offers researchers tools that reveal key dynamical properties associated with *emergence*: "A phenomenon is emergent when it originates in the cognition, affect, behaviors or other characteristics of individuals, is amplified by their interactions, and manifests as a higher-level, collective phenomenon (Kozlowski and Klein, 2000, p. 55)." Collaborative learning processes and team knowledge outcomes are emergent phenomena in team contexts, as these are shaped by individual learning and interactions (Anderson and Lewis, 2014). Importantly, Kozlowski *et al.* (2016) point out that team-emergent processes interact with a team's structure and context to produce system-level behavior that is fundamental for understanding organizational behaviors as multilevel phenomena.

This paper provides a unique contribution to the literature by: (i) demonstrating how a hybrid approach using SFM, ABM and SNA can synergistically leverage each other's strengths to more realistically represent team behavior; and (ii) revealing new insights about the interactive and dynamic effects of individual knowledge, dyadic communications and team structures, for team performance. Our model and findings can apply to many

[1]We use "stock-and-flow" in this paper to represent the differential equation models that are most commonly seen in the system dynamics literature (for examples, see Forrester, 1958, 1961; Sterman, 2000). We choose this name to avoid confusion with (1) multi-agent models such as those in Nelson and Winter (1982) or any other models that employ multiple, nonlinear feedbacks such as those found in the discrete-event simulation literature described in Heath *et al.* (2011).

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sorts of teams assembled to tackle complex and information-intensive problems, such as product development teams, project teams and top-management teams. In addition, our approach may be scalable to arbitrarily larger units such as divisions and firms because their relationships are often analogous to those between team members and the team as a whole (Argote, 1999).

In the next section, we contrast aspects of the three modeling methods of interest and discuss how each can complement the other effectively. Following that discussion, we articulate research questions that we investigate using the hybrid model. We offer a proof-of-concept that addresses these research questions and examines how team member attributes and emergent relationships contribute to team performance over time. We then present the results of a simulation study that shows how the hybrid approach can provide novel, interesting insights into these and other team science questions. Following sensitivity studies of the hybrid model, we conclude the paper with a discussion of implications for theory, limitations and potential extensions. Items of a technical nature, such as a table comparing the three modeling methods, base model parameters and additional sensitivity analyses are presented in the Appendix.

Leveraging three different modeling methods

Across disciplines, there has been an increasing interest in combining different simulation methods (e.g., Rigaux *et al.*, 2001). More familiar to a system dynamics audience, Metcalf and Paich (2005) studied spatial dynamics in urban growth, and Rahmandad and Sterman (2008) compared SFM and ABM models in epidemiology. To understand the potential for synergies between the three modeling methods, we build upon prior comparative studies by contrasting SFM, ABM and SNA *within the specific context of team science.*

To be sure, each of the methods, with enough manipulation, can replicate any other; for example, each method can account for interpersonal interactions. The methods, however, are not identical in their strengths (Rahmandad and Sterman, 2008; Heath *et al.*, 2011; Zhang *et al.*, 2015). For example, SFM contributes the ability to model both high-level system feedback loops and individual-level feedback loops, state variable inertia, continuous variables and their dynamic interplay (Anderson and Lewis, 2014). It also provides a well-defined library of modeling templates, such as those for productivity, which correspond tightly to real-world measures at the aggregate level (Sterman, 2000). SFM can also be adapted to the individual level in a straightforward manner, as exemplified in this paper's model of individual productivity. SNA provides a template for analyzing relationships between individuals (Wasserman and Faust, 1994), while ABM contributes

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the ability to model individual agent attributes. ABM also provides for "simple-rule" low-level interactions among heterogeneous agents to account for dyadic interactions—a useful supplement to SFM and SNA when modeling team behavior (Ren *et al.*, 2006). Finally, ABM and SFM generally operate at the time series level and use continuous variables (or at least discrete approximations; Forrester, 1958; Nan, 2011). In contrast, only a small minority of SNA research studies capture the fine-grained dynamics of system evolution. Moreover, most SNA research uses dichotomous, rather than continuous, tie strengths. Continuous tie strength is highly valuable in a team context because the relatively few ties possible among a small number of team members can create significant distortions, as we show in the sensitivity analysis later in this paper. We summarize the capabilities for each method for modeling team processes and performance in the Appendix.

By combining aspects of SFM, ABM and SNA into a *hybrid model*, we can leverage the strengths of these methods to study the interdependencies that may frustrate a researcher trying to simulate complex team behavior and performance. The closest approaches to our proposed hybrid model come from two streams of literature. First, Carley and her co-authors have explicitly studied team performance versus team structure using ABM models (Carley and Lin, 1995; Carley and Svoboda, 1996; Lin and Carley, 1997). These innovative models measure accumulated team performance at the end of simulation runs. We build on their work by also characterizing transient behavior over time, e.g., short-term versus long-term team performance. Second, research on dynamic networks by Snijders and his colleagues used simulations with accumulating ties to study the evolution of network nodes and ties (Snijders, 1996; Burk *et al.*, 2007; Snijders *et al.*, 2010). These and other dynamic network studies are especially effective at estimating how the propagation of valued resources (e.g., people, information, technological adoption) unfolds across large networks. We build on their work by representing the collective (team) level of analysis as a dynamic network that evolves under specified conditions. Finally, we build on both streams by including the feedback of collective team behavior upon individuals and ties and vice versa.

Team science research questions: a proof-of-concept of the hybrid model

In this section, we lay out three research questions about team science that we later simulate with the hybrid model. While some of these research questions have been examined in past empirical research, they are rarely investigated in concert, potentially masking important intertwining and dynamic effects.

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The first research question addresses the effects of too much specialized learning (individual knowledge overspecialization) on collective knowledge and productivity. Overspecialization is a risk in teams that rely on members' expertise to perform well. Over time, members' expertise may become extremely specialized, leading to reduced collective performance over time. Anderson and Lewis (2014) earlier showed via simulations that individual knowledge specialization is beneficial to productivity up to a point, but that further specialization (overspecialization) can eventually impede collective learning. Their simulation results corroborate arguments by others, who suggest that overspecialized individuals may come to lack enough generalized knowledge to cooperate and communicate as effectively with other members (Wegner, 1986; Schilling *et al.*, 2003; Fraidin, 2004). *Does the hybrid model, with its more nuanced specification of both individual and collective knowledge, produce similar results?* If it does, then we can be fairly confident that the hybrid model specifications are consistent with the theoretical and empirical predictions about knowledge overspecialization.

Second, we explore the effects of a team's communication network structure on learning and productivity. Both Palazzolo *et al.* (2006) and Lee *et al.* (2014) found that certain communication patterns are linked with efficient information exchanges and the development of collective knowledge. However, much of the research on team information exchange has emphasized flat team structures as opposed to the hierarchical structures that are very common in organizational teams (e.g., Carroll and Gillen, 1987; Ahuja and Carley, 1998). *How do dynamic tie networks affect individual and collective learning and productivity?* We advance the model from Anderson and Lewis (2014) by simulating effects of team hierarchy on communication patterns, individual learning and collective learning on productivity. This capitalizes on the strengths of the proposed hybrid model because tie strengths, the building blocks of collective learning, are represented as relations between individuals that can vary over time.

Third, we illustrate the usefulness of the hybrid approach for understanding how member similarity (or heterogeneity) affects emergent dyadic and team structures. Past empirical research on team diversity suggests that the degree to which members perceive themselves as similar or different will affect the emergence of patterns of interactions among members and team structures. For example, perceived diversity can reduce communication and information sharing among members (Lau and Murnighan, 1998, 2005; Gibson and Vermeulen, 2003), which can eventually divide the team into one or more subgroup structures. One stream of research characterizes these effects in terms of *faultlines* that divide members. Faultlines are the result of the alignment of multiple diversity characteristics, such as gender, educational background or any other characteristic that members perceive as different. For example, a faultline might develop in a team with males and females, when the males are also different from the females on some other variable

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such as educational background. We pose the following research question, which we investigate with the hybrid model: *How do diversity-based subgroups, which can exacerbate so-called faultlines (*Lau and Murnighan, 1998*), interact with formal team structures (hierarchies) over time?*

Extant research exists with respect to the role of diversity-based subgroups and the concurrent development of faultlines (as well as the factors that can dismantle faultlines) (e.g., Gibson and Vermeulen, 2003; Ren *et al*., 2014). However, that research is limited by a static view of the problem that ignores temporal tradeoffs that might explain when diversity is helpful versus harmful to team productivity. For example, members of the same subgroup may find it easier to communicate with each other (Gibson and Vermeulen, 2003). However, if all members are similar with respect to training or skillsets, the requisite diversity to solve problems and thus be productive may be lacking (Ashby, 1958; Ancona and Caldwell, 1992). *We hypothesize that examining the impacts of diversity with the dynamic framework of a hybrid model may show that both of these viewpoints are correct, but at differing moments in time.* At a more nuanced level, we also inquire into how the positioning of team members from different subgroups *within the hierarchy* influence team performance. The literature in this area is sparse, such that specific results with respect to clustering members from the same subgroup versus dispersing them do not exist and resulting theory generally needs to be extrapolated. For example, Bezrukova *et al*. (2009) and Carton and Cummings (2012) argue that identification with a team ameliorates performance issues resulting from faultlines between subgroups. This would suggest that dispersing team members from different diversity-based subgroups throughout the team (i.e., to avoid clustering) might be desirable, because it would promote team identification. Ren *et al*. (2014) partially support this extrapolation by finding that ties between members of different subgroups improve team performance, which would also suggest an advantage of dispersion. Somewhat in contrast, Meyer *et al*. (2015) argue that individual performance in a team improves when the team leader is of the same subgroup. This might be extended to argue that clustering team members of the same subgroup together might improve overall team performance. In any case, both of these viewpoints are based on cross-sectional studies that provide only a static view of the problem.

A hybrid model: model overview

To address the goals of this paper and investigate these research questions, we extend the simulation model published in Anderson and Lewis (2014), which itself was an advance in understanding the dynamic interplay between individual and collective (team) learning. In their model, the knowledge stock used in conventional models of learning (e.g., Argote, 1999)

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was decomposed into two distinct stocks: one representing an accumulation of individual knowledge and the other an accumulation of collective knowledge. In a departure from other team learning studies (e.g., Reagans *et al.*, 2005), Anderson and Lewis (2014) show that learning at different levels of analysis is intertwined; that is, learning at the collective level affects learning at the individual level, and vice versa, to affect productivity. The temporal cause-and-effect relations between variables in the model are guided by theory and by empirical evidence from the literature (Lewis et al., 2005, 2007; Burton and Obel, 2011). The theoretical foundation for the model is transactive memory system (TMS) theory, which is used to explain the dynamic interplay of individual knowledge acquisition and collective knowledge and structures (Wegner, 1986; Lewis *et al.*, 2005). A TMS is a shared memory system for managing and communicating information, which encourages complementary specialization of individuals' knowledge to improve overall collective performance (Liang *et al.*, 1995; Moreland, 1999; Lewis, 2003). According to TMS theory, interdependent individuals come to divide the cognitive labor for a task, such that different individuals develop distinct expertise, which can be accessed via inter-member communication. The functioning of a TMS depends on individuals sharing a mental "directory" of who knows what in the team, so that task-relevant knowledge can be retrieved and brought to bear on the team's tasks. Research on TMS has shown, in a variety of contexts, that teams that develop a TMS collectively recall and apply a greater amount of knowledge, coordinate their interactions more effectively and perform at higher levels compared to teams without a TMS (Lewis and Herndon, 2011; Ren and Argote, 2011).

The Anderson and Lewis (2014) model leveraged TMS theory to specify how collective knowledge about "who knows what" influences learning at the individual level and vice versa. In the current paper, we add to that model in several important ways. First, we represent the individual contribution to the production function not as an aggregate knowledge stock, but as a vector of individual knowledge stocks. In specifying individual knowledge as a vector, we introduce the possibility that different individuals may differ in their knowledge and, via learning curve theory, their capabilities (Argote, 1999). This ABM-like specification allows for differences in members' capabilities to affect model behavior. We also follow SFM practice, however, by modeling both each individual knowledge and tie strength variable as an accumulation.

Second, we characterize collective knowledge not as a single aggregate stock, but rather as a function of an $N \times N$ matrix of stocks representing communication ties between members. This SNA-like characterization of collective knowledge is consistent with decades of social network research, which considers networks a form of social capital (Bourdieu, 1986; Burt, 1992), defined as the sum of the actual and potential resources embedded within, available through and derived from relational ties. Networks afford access to

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valued resources like knowledge via communication ties (Levin and Cross, 2004), which provide not only task-relevant information but also information about the location of knowledge. Research by Yuan *et al*. (2010) demonstrated that the strength of communication ties between members is related to the development of a shared understanding of who knows what—a form of collective knowledge embedded in a TMS. The similarity between knowledge networks and TMS was again highlighted by Lee *et al*. (2014), who argued that the collective knowledge embedded in a TMS is akin to a collective knowledge network that links members via communication ties. These and other research findings provide strong support for specifying collective knowledge as a network.

Third, the hybrid model accounts for the notion that the *structure* of the communication network matters—evidence from social network and small groups research suggests that certain communication patterns are more advantageous than others. In particular, network structures with many *transitive triads* are associated with efficient and effective information exchange, which can increase collective performance (Palazzolo *et al*., 2006; Lee *et al*., 2014). A *transitive triad* network structure exists if, whenever person *i* is linked to person *j* and person *j* is linked to person *k*, then person *i* is linked to person *k*. "By simultaneously including (i) a common party connecting two members; and (ii) a connection between two remaining members who receive information from a common third party, the transitive triad combines efficiency and balance, maximizing coordination of information exchanges among team members" (Lee *et al*., 2014, p. 954). Thus we leverage the Anderson and Lewis (2014) model and add new specifications to more fully account for member variation and member interdependencies (via communication ties). As we show later, this hybrid model allows us to simulate the complex, dynamic effects of both individual and collective learning under conditions faced by real-world teams.

The variables in this model and their basic dynamic relationships can be elegantly represented using a causal loop diagram from the SFM approach in Figure 1. The basic outcome of interest with respect to teams and teamwork is *performance*, represented here as the rate at which tasks are completed in the team (Team Productivity), which is at the center of the diagram. Also represented in the model are two outcomes of *learning*: one (Individual Knowledge for each team member, which is a vector, in loops R2 and B2), which directly contributes to Individual Productivity; the other (Tie Strength, which represents the tie between each pair of team members in a Matrix, in loops R1 and B1) represents how effectively the team member contributes to collective learning via her individual *embeddedness* in the team's communication network. We define an individual's embeddedness as the degree to which an individual is connected with other team members via her accumulated dyadic ties. As tasks are completed by the team, both rates of learning and knowledge accumulation are affected, shown in the diagram

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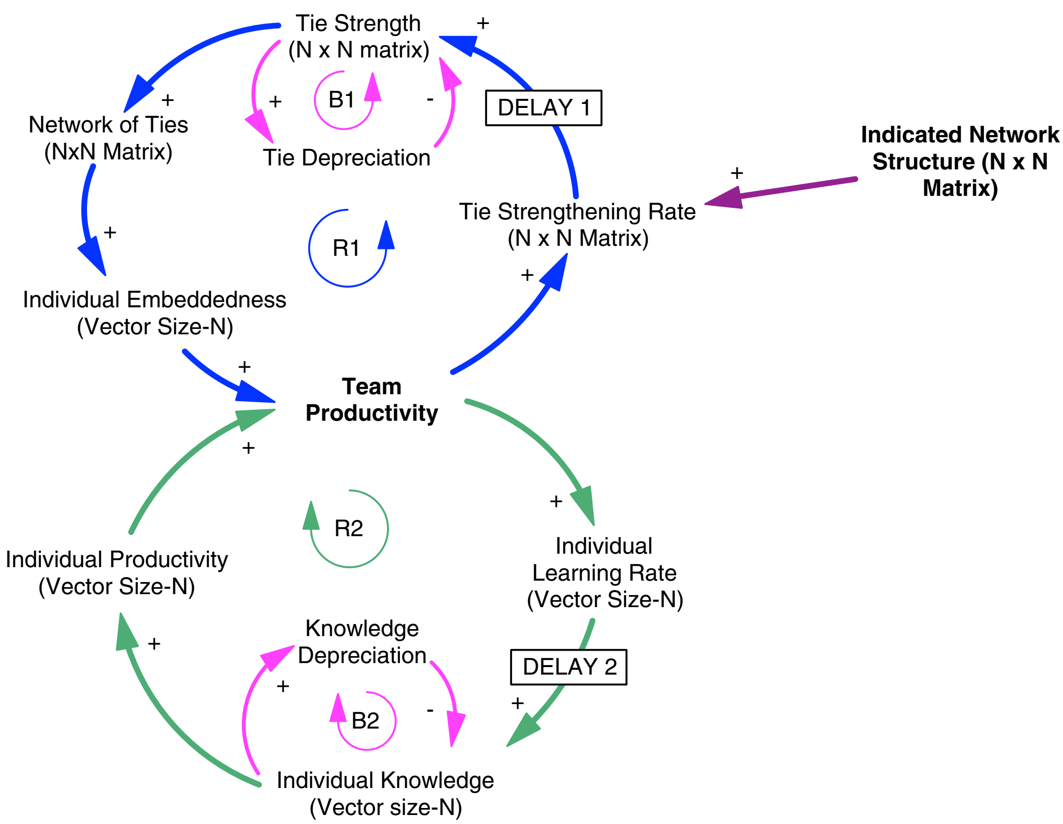

Fig. 1. CLD of base model [Color figure can be viewed at wileyonlinelibrary.com]

as reinforcing loops R1 and R2. (For this reason, in the model we use the units of “tasks” for both variables, consistent with past tie strength measures in organizational networks (Borgatti and Cross, 2003; Borgatti and Foster, 2003). The rate of tie accumulation is also influenced by the *indicated network structure*, which could represent formal communication networks within a team. Specifically, the rate at which individuals learn and the rate at which communication network ties are strengthened affect the accumulation of individual knowledge and collective knowledge. Increases in an individual’s knowledge will increase that individual’s productivity, which in turn increases team productivity (R2). Increases in the strength of certain ties can increase individual embeddedness, resulting in a dynamic network structure reflecting a particular pattern of ties (R1). In some cases, the particular pattern of ties is advantageous and in some cases the pattern is disadvantageous. Research on network structures, for example, finds that a

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structure with many transitive triads (Simmel, 1950; Obstfeld, 2005) can increase the productivity of the team as a whole (Lee *et al.*, 2014), which in turn increases the team's collective capability to complete tasks. The balancing loops B1 and B2 represent knowledge depreciation (forgetting), which is inherent to both individual and collective cognitive processes (Epple *et al.*, 1991; Cohen and Bacdayan, 1994; Argote, 1999).[i]

To make the application of the hybrid model more concrete, we provide an illustrative example of how the model might play out in a real team. Imagine a team of seven engineers assembled to develop the hardware components for a robotic device. Let us assume that the members of the team possess some expertise needed for the team's tasks, and that members' expertise must be utilized and combined effectively for the team to perform well. Thus members must share knowledge and communicate with, and synthesize information from, the appropriate members in order to increase learning and productivity. One could imagine the tasks of this team to be focused on development and design, prototyping, testing and integrating component systems. As the team completes its tasks, individual members accumulate knowledge, which increases each member's capacity for productivity. As the team completes tasks, members may communicate and share knowledge with all, or only some, of the other members during task completion—producing a dynamic pattern of ties that (i) alters the individual embeddedness of team members; and (ii) affects the team's ability to consider, combine and apply each member's individual capacities for collective productivity.

Mathematical specification

Team productivity

The basic model described above is now translated into mathematical equations. The core equations of interest will be presented in this section. (A detailed description of the full model is in the Appendix.)

Let

$p(t)$ = team productivity in tasks completed per week at time t;
p_0 = initial team productivity.
$a(t)$ = the effect of the collective upon productivity at time t;
$i(t)$ = the effect of individual knowledge on productivity at time t.

For convenience and without loss of generality, we set $p_0 = 1$. Following Anderson and Lewis (2014), the productivity at time t is

$$p(t) = p_0 a(t) i(t) = a(t) i(t) \tag{1}$$

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Note that the formulation in Eq. (1) will be described at a more granular level in the sections that follow. Specifically, $i(t)$ is defined below as a function of a member's individual knowledge and the strength of her ties to other members, and $a(t)$ is defined in terms of an SNA structure of $N \times N$ ties, per Figure 1.

Individual productivity

To model this, we follow the well-known "learning curve" or "learning by doing" literature as a proxy for productivity. Wright (1936) is the seminal author documenting this relationship. (See Argote, 1999, for a review of the literally hundreds of articles in this stream of literature, including the application of the learning curve to teams and team members.) We follow Anderson and Lewis (2014) and Epple *et al.* (1991) by relating the individual knowledge stock and parameters in a learning curve, such that each team member's experience increases linearly with each additional task completed. We also follow that literature in assuming that older experience will become less relevant with time to future productivity. For example, in our illustrative robotics team, new technology for designing robots will eventually obsolesce experience with older technology.

Let

N = the number of individuals within the team;

$\mathbf{k^i}(t)$ = a vector of dimension N, where $k_j^i(t)$ represents individual j's knowledge—for example, in tasks completed, at time t, where $j \in \{1 \ldots N\}$. Note that the superscript i represents a variable representing or affecting individual-level, rather than tie-level, variables or effects;

$\mathbf{c^i}(t)$ = a vector of dimension N, where $c_j^i(t)$ represents individual j's number of "learning units" of individual knowledge accumulated per completed task at time t (for now all $c_j^i(t)$ are set equal to one as there is no differentiation until we examine specialization in a later section);

$k^i(0)$ = the individual's cumulative individual knowledge at time 0 (this is the same for all $j \in \{1 \ldots N\}$);

χ^i =the fractional rate at which individual knowledge is "forgotten";

γ^i = individual learning parameter, $0 \le \gamma^i \le 1$.

Following Epple *et al.* (1991) and Reagans *et al.* (2005), we rewrite $i(t)$ in Eq. (1) in a learning curve formulation, as shown below. Let

$$i_j(t) = \left[\frac{k_j^i(t)}{k^i(0)}\right]^{\gamma^i} \text{ for all } j \in \{1 \ldots N\} \tag{2}$$

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Again following Epple *et al*. (1991), we account for knowledge depreciation by writing the change in each individual's stock of knowledge as

$$\frac{\mathrm{d}\mathbf{k^i}(t)}{\mathrm{d}t} = p(t)\mathbf{c}^{\boldsymbol{i}}(t) - \chi^i\left[\mathbf{k^i}(t) - k^i(0)\right] \tag{3}$$

Collective learning

We now turn to the specifications related to collective learning. As individuals interact with each other in the course of completing tasks, the ties between individuals can strengthen. The network of communication ties that results from task completion is a manifestation of collective knowledge (Burt, 1992; Lee *et al*., 2014), modeled as an SNA structure of $N \times N$ ties. In our robotics team example, each tie might represent the frequency of task-relevant communication between each pair of team members.
Let

$\mathbf{A}(t)$ = an $N \times N$ matrix, where $A_{j,k}$ represents the tie strength of the directed arc from individual j to individual k—which can occur as an accumulation of communication, interactions, etc.—proportionate to the number of tasks completed together—at time t, where $j,k \in \{1 \ldots N\}$ Note: $A_{j,k} = 0$ if $j = k$ for all t as an individual cannot have a tie with himself;

$\mathbf{A}(0)$ = an $N \times N$ matrix, where $A_{j,k}$ represents the initial tie strength of the directed arc from individual j to individual k at time 0;

$\mathbf{C^a}(t)$ = an $N \times N$ matrix, where $C^a_{j,k}(t)$ represents the indicated network structure from individual j to individual k at time t, where $j, k \in \{1 \ldots N\}$ can represent communication or work networks (formal, informal, etc.) that moderate the accumulation of tie strength. Note: $C^a_{j,k}(t) = 0$ if $j = k$ as an individual cannot have a tie with herself. Also note that the superscript a indicates a variable representing or affecting tie-level, rather than individual-level, variables or effects;

χ^a = the fractional rate at which a tie's strength deteriorates or is "forgotten".

The key idea is that tie strengths are the accumulation of task-relevant communications as tasks are completed over time. In other words, ties take time to accumulate strength, and they can deteriorate if no interactions take place. The robotics team example provides an illustration—a team member's recent communications with other members is likely to provide better information about others' capabilities than would older communications, which may have faded from memory or become supplanted by updated information about which member possesses what knowledge. The accumulation of those

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ties is also influenced by an *indicated network* $\mathbf{C}^{\mathbf{a}}(t)$. As we explained earlier, the indicated network represents an initial pattern of relationships between members. The initial pattern of relationships could reflect a formal hierarchical team structure (i.e., one that restricts communication between a manager and a few subordinates), or the ease with which members are able to communicate, say, because members are colocated. In any case, the indicated network structure may promote or hinder subsequent tie development between specific pairs of team members. To model the evolution of the tie strengths, we analogize from Eq. (3):[ii]

$$\frac{\mathrm{d}\mathbf{A}(t)}{\mathrm{d}t} = p(t)\mathbf{C}^{\mathbf{a}}(t) - \chi^{a}[\mathbf{A}(t) - \mathbf{A}(0)] \tag{4}$$

To represent the effect of the pattern of communication ties (network structure) that emerges from inter-member interactions, we can employ any number of theoretically or empirically validated network structure measures in the function. We employ a measure of a particular network structure: the number of transitive triad structures in a communication network, which has been found in empirical research to be positively related to the development of a TMS, which in turn positively impacts team performance (Palazzolo *et al.*, 2006; Lee *et al.*, 2014). As Lee *et al.* (2014) explain, the transitive triad structure is an especially useful one for helping a TMS to develop because an individual embedded in a triad structure is in a position to encourage, facilitate and coordinate information exchanges between two other individuals. The focal individual in a triad structure is referred to as a "tertius"—Latin for "the third". An individual in the tertius position is the most embedded in the triad structure and has the most accurate knowledge about the expertise of other members in the triad (being connected to the other two members, who might not initially be connected to each other). Thus the tertius is in the most advantageous position for guiding the flow of information in the triad, helping other members learn about who knows what, and creating a shared understanding that fuels TMS development. Indeed, results from Lee *et al.*'s (2014) study show that teams whose communication patterns reflect transitive triad structures are more likely to develop a TMS and to perform at higher levels as a result. The number of transitive triad structures in the team's communication network strongly affects the capacity of a team to complete tasks.

We build on the research above, which generally regresses team productivity simply on *the total number of transitive triads in a team*, to count transitive triads for each *individual* team member. Specifically, we define each team member's *individual embeddedness by counting the number of triads in which she, as an individual, is a tertius.* First, we normalize each tie's strength to lie within the interval [0, 1]. This specification allows for tie strength to be a continuous value, rather than a dichotomous one, which is

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common in SNA research (Wasserman and Faust, 1994). Our specification answers calls from the SNA literature to measure ties with greater nuance and validity than dichotomization allows (Opsahl and Panzarasa, 2009). Let.

$\mathbf{A}^{\boldsymbol{n}}(t)$ = an $N \times N$ matrix, where $A^n{}_{j,k} = f(A_{j,k}, A^*)$, where the function f maps $A^n{}_{j,k}$ into the interval [0, 1] (A^* can be roughly thought of as the point where the accumulation of interactions in Eq. (4) results in an effective tie).

A convenient operationalization of f for use in the simulation of the model is an exponential curve (Sterman, 2000). This formulation normalizes how strong the tie is between a pair of team members on a scale of zero to one. In our robotics team, for example, some members directly communicate continually, some never at all. For the former case, the tie strength is close to one. In the latter, the tie strength between those members will be zero. Importantly, this normalized tie strength could be a partial value such as 0.4. Let.

$f(A_{j,k}, A^*)$ = the function normalizing the strength of a tie;
A^* = the reference tie strength for normalization.

$$f\left(A_{j,k}, A^*\right) = 1 - \exp\left(-\frac{A^n{}_{j,k}}{A^*}\right) \text{ for all } j,k \in \{1..N\} \tag{5}$$

Then the number of transitive triads can be found by letting.

$\boldsymbol{\Lambda}(t)$ = an $N \times N \times N$ matrix, where $\Lambda_{j,k,m}(t)$ =1 if j, k and m are distinct and there is a transitive triad such that directed arcs exist: $j \rightarrow m$, $k \rightarrow m$ and $j \rightarrow k$. If so, $\Lambda_{j,k,m}(t)$ =1, otherwise, $\Lambda_{j,k,m}(t)$ = 0 (note that this makes node m the "tertius").

In the model, we again avoid dichotomization issues when counting transitive triads by operationalizing a transitive triad as

$$\Lambda_{j,k,m} = A_{j,m} A_{k,m} A_{j,k} \quad \text{for all} \quad j,k,m \in \{1..N\} \text{ and } j \neq k, k \neq m, j \neq m \tag{6}$$

Let

$k^a_m(t)$ = the number of triads in which m is a tertius.

Then we represent the individual embeddedness of each team member as

$$k^a_m(t) = \sum_{j,k} \Lambda_{j,k,m}(t) \quad \text{for all} \quad j,k,m \in \{1 \ldots N\} \tag{7}$$

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We remind readers that the above specification reflects the *position* of a given member in the communication network. A member's network position affects the degree to which that member can access information possessed by other members and regulate information flow between other individuals in the triad. If an individual m is the tertius in several transitive triad structures, that individual is highly embedded, able to coordinate and leverage knowledge flows among a greater number of team members, potentially increasing collective productivity (Lee *et al.*, 2014). Thus the number of triads in which each team member is a tertius indicates the extent to which the structure of the communication network will increase the capacity of the team to be productive. Like individual-level knowledge, the capacity of the individual to contribute to team productivity via the communication network is also prone to learning effects. Hence it is reasonable to rewrite $a(t)$ in Eq. (1) to follow a learning curve formulation for each individual as shown below. Let.

γ^a=the "learning curve" parameter for individual embeddedness, $0 \leq \gamma^a \leq 1$.

$$a_j(t) = \left[\frac{k_j^a(t) + k^{a^*}}{k^{a^*}}\right]^{\gamma^a} \text{ for all } j = \{1 \ldots N\} \tag{8}$$

(Note that k^{a^*} is included in the definition above to keep Eq. (8) well behaved.)

Team productivity at the granular level

Combining individual productivity and embeddedness into each individual's contribution to team productivity, we restate Eq. (1) as follows:

$$p_j(t) = a_j(t) i_j(t) \text{ for all } j = \{1 \ldots N\} \tag{9}$$

Now we can model the production function of the team as

$$p(t) = \frac{1}{N} \sum_j p_j(t) \text{ for j} = \{1 \ldots N\} \tag{10}$$

Connections among the three methods

Equation (10) is crucial because it links the productivity of individuals, which is primarily at the agent and tie levels, into an aggregate variable, all of which are embedded in a feedback loop. Moreover, ABM and SNA

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elements are tied together in an SFM feedback loop exemplifying the hybrid nature of this model.[iii] The hybrid nature of the model can be seen in the fact that almost all the equations reflect an interplay between at least two of the methods. Eqs (2), (3) and (8) are primarily agent-level equations, although using a formulation commonly seen at the aggregate level in the SFM literature (Anderson and Parker, 2002). Further, Eq. (3) involves an aggregate variable $p(t)$ characteristic of SFM. Equations (4) and (5) are derived from the SNA literature but are instantiated using ABM and SFM in an analogous manner. Equations (6) and (7) are SNA based. Equations (9) and (10) are together a production function. Production functions are economic constructs typical of SFM models (Thompson, 1981; Sterman, 2000), but are instantiated in this case by aggregating agent-based characteristics.

A note on stochasticity

Some readers of this article familiar with ABM modeling may be curious as to the lack of stochastic elements in this model. We follow the SFM tradition in this model and avoid introducing stochastic elements, when possible, so as to focus on the effects of the structure on the dynamics of the model (Sterman, pers. comm. 1996, 2000).

Simulation analyses

Specialization and overspecialization

The basic model presented earlier is designed to represent (and discern) the effects of individual embeddedness within the team upon productivity. As mentioned earlier, one property of interest is a team's TMS, which is a function of individuals' embeddedness within the team structure. Other, more complex relationships that affect emergence can also be modeled. For example, the TMS literature suggests that one pitfall of developing TMS is the overspecialization of members, who might come to lack enough generalized knowledge to cooperate and communicate as effectively with other members, thus reducing team effectiveness (Wegner, 1986; Schilling *et al.*, 2003; Fraidin, 2004). At the same time, specialization is one mechanism through which TMS benefits team performance (Anderson and Lewis, 2014). To show the beneficial effect of member specialization resulting from TMS, we model this by following Anderson and Lewis (2014) by letting.

$g\left[k_j^a(t)\right]$ = the effect of specialization on individual knowledge;
σ = the specialization parameter such that $0 \le \sigma < 1$;
k^{a^*} = the reference value for normalization of $k_j^a(t)$.

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Then

$$g\left[k_j^a(t)\right] = \left(1 + \frac{k_j^a(t)}{k^{a^*}}\right)^{\sigma} \text{for all}\, j \in \{1 \ldots N\} \text{ such that } 0 \le \sigma < 1 \tag{11}$$

There are limits to the benefits of specialization. For example, a team member can only specialize effectively if she knows the capabilities of a number of other team members well (i.e., she is highly embedded in the team communication network). In a team of ten, knowing about the expertise of two other members is much more useful in the decision to specialize than is knowing about only one other member's expertise. However, if a member knows the expertise of nine members, it is intuitively almost as useful as knowing all ten. We capture this by restricting σ to be less than one. This creates a monotonically increasing relationship with diminishing returns resulting from specialization, which agrees not only with our example but also with much of the literature on specialization (Ellis, 1965). We also set the minimum at one rather than zero so that Eq. (3b) below cannot create a situation in which a team member's knowledge is forever "stuck" at zero. k^{a^*} is a constant used to normalize the effect of the function in Eq. (11) (one can think of k^{a^*} as roughly the point above which the specialization effect "kicks in").

$$\frac{\mathrm{d}\mathbf{k}^{\mathbf{i}}(t)}{\mathrm{d}t} = p(t)g\left[k_i^a(t)\right] \mathbf{c}^{\boldsymbol{i}}(t) - \chi^i\left[\mathbf{k}^{\mathbf{i}}(t) - k^i(0)\right] \tag{3b}$$

Importantly, Eq. (3b) effectively links a construct that is more SNA-like ($k_i^a(t)$) in this model with an ABM-like construct ($\mathbf{k}^{\mathbf{i}}(t)$). Moreover, the relationship between the two constructs creates a high-level feedback typical of SFM-like models. Thus all three modeling traditions are linked.

Overspecialization, in contrast, diminishes increases in tie strengthening because communication between individuals diminishes due to accumulated functional differences (Schilling *et al.*, 2003; Fraidin, 2004). Following Anderson and Lewis (2014), we model this effect with a reverse logistic "s-curve" to make this relationship rational for extreme values and monotonically decreasing (Repenning, 1996, p. 14). As an example, all the engineers in our illustrative team are hardware engineers. However, the more one engineer specializes in project management and another engineer specializes in the technical development of (say) a servomechanism control, the less common ground they have to discuss their issues, and, more importantly, evaluate each other's capabilities. This problem has long been recognized in the project management literature (e.g., Schilling *et al.*, 2003). We capture this by letting individuals' experience on both sides of a tie affect the tie's evolution. Let.

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$H^a_{j,k}(t)$ = the effect of overspecialization on tie strength accumulation;
ω = the overspecialization parameter;
$k^{i^*}_1, k^{i^*}_2$ = the reference value for normalization of $k^i_j(t), k^i_k(t)$ respectively.

Then

$$H^a_{j,k}(t) = \left\{ 1 - \frac{1}{1 + e^{-\omega\left[\frac{k^i_j(t)}{k^{i^*}_1} - \frac{1}{2}\right]}} \right\} \cdot \left\{ 1 - \frac{1}{1 + e^{-\omega\left[\frac{k^i_k(t)}{k^{i^*}_2} - \frac{1}{2}\right]}} \right\} \text{for all } j, k \in \{1 \ldots N\} \quad (12)$$

The first factor in the equation reduces communication from team member j to k if j is overspecialized using a reverse S-curve; the second factor does the same if k is overspecialized. If either or both are true, $H^a_{j,k}(t)$ reduces from one to zero, thus reducing any increase in tie strength between the two. We note that the minimum of $H^a_{j,k}(t)$ can be raised from zero to some intermediate level, but robustness tests show that the simulation results below are not qualitatively affected.

We can then rewrite Eq. (4) as

$$\frac{\mathrm{d}A_{j,k}(t)}{\mathrm{d}t} = p(t) H^a_{j,k}(t) C^a_{j,k}(t) - \chi^a \left[A_{j,k}(t) - A_{j,k}(0) \right] \text{for all } j, k \in \{1 \ldots N\} \quad (4b)$$

The constants $k^{i^*}_1$ and $k^{i^*}_2$ are used to normalize the effect of the reverse S-curve functions, becoming, in effect, the points at which the overspecialization effect "kicks in" on each side of the tie. The constant ω represents the "sharpness" of the cutoff around $k^{i^*}_1$ and $k^{i^*}_2$. For this paper, we keep $k^{i^*}_1 = k^{i^*}_2$ to preserve symmetry, although this is not necessary. Typical values for ω in Eq. (12) that will produce reasonable behavior are between 3 and 10 (Anderson and Lewis, 2014). Repenning (1996, p. 14) used ω = 4. The CLD of the resultant model is shown in Figure 2.

Before simulating the effects of specialization and overspecialization, it is necessary to describe the indicated network structure $\mathbf{C^a}(t)$ that moderates the rate of tie strengthening. Recall that the indicated network structure represents an initial pattern of relationships between members. We have chosen a simple hierarchy (Figure 3) as the indicated network structure throughout the paper because of how common it is in organzations. This simple hierarchy is a stylized group structure meant to illustrate cases in which members' communication ties vary in strength (a realistic assumption; see, for example, Carroll and Gillen, 1987), depending on the frequency with which members communicate. While such a hierarchy could imply formal reporting relationships, the hierarchy more generally reflects communication patterns

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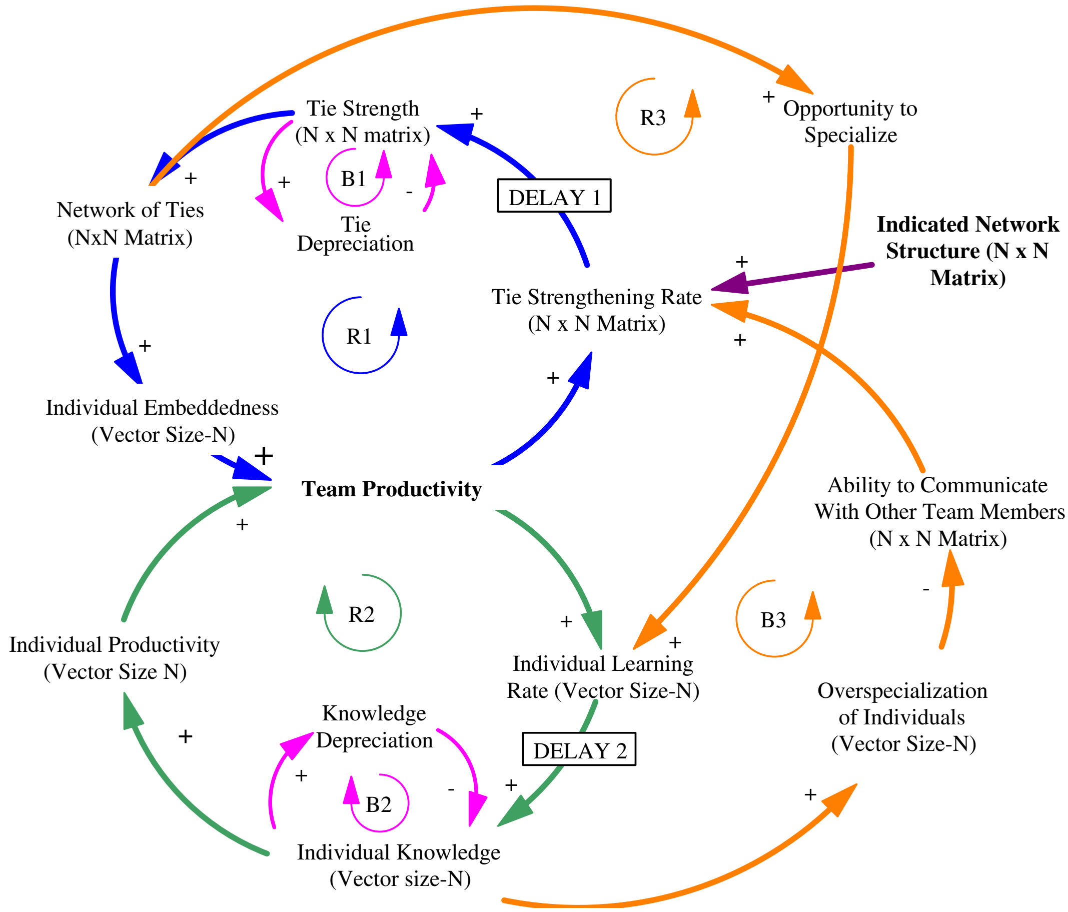

Fig. 2. CLD with specialization and overspecialization effects [Color figure can be viewed at wileyonlinelibrary.com]

that might exist in a group (Weber, 1947; Ahuja and Carley, 1998; Monge and Contractor, 2001). In this paper, we follow this stream of literature by considering only communications ties. *We ignore any ties resulting from power differentials or decision rights.*

The indicated network that represents these relationships, $\mathbf{C^a}(t)$, whose elements can designate such things as the relative number of communications completed per task, is represented in the model by each element of $\mathbf{C^a}(t)$ having a consistent positive value C^{a^*} for all t in the matrix for each digraph represented in Figure 3, and a value of 0.0 for each digraph not represented in that figure. Thus, for example, $C^a_{1,2}(t) = C^a_{2,1}(t) = C^{a^*}$, but $C^a_{5,6}(t) = C^a_{6,5}(t) = 0$.

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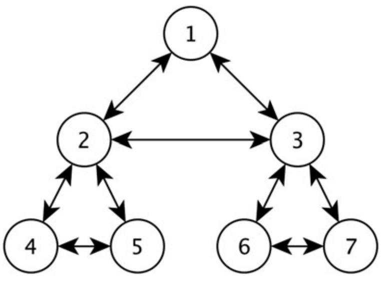

Fig. 3. Hierarchy used in this model throughout the paper

To illustrate the potential results of specialization and overspecialization and address our first research question, consider the simulations shown in Figure 4a–c. The three runs show the effects on the model when: (Case 1) no specialization or overspecialization is possible, i.e., Eqs (3) and (4) are used; (Case 2) only specialization occurs, i.e., Eqs (3b) and (4) are used; and (Case 3) both specialization and overspecialization occur, i.e., Eqs (3b) and (4b) are used.

Examining Figure 4a, for Case 1, in which no specialization or overspecialization is possible, the typical learning curve occurs with diminishing returns from knowledge depreciation beginning in months 14–16. In contrast, in Case 2 there is an acceleration of learning due to the specialization effect after month 4. In Case 3 there is also an initial acceleration due to specialization after month 4. However, the overspecialization effect prevents the wild productivity growth of Case 2. After month 8, in Case 3, team productivity begins to level off. After month 13 it actually begins to lag the base learning curve presented in Case 1 and then declines. Overspecialization causes the anticipated diminishing returns from knowledge in the rate at which tasks are completed by the team, but overspecialization also induces a long-run decline in team productivity after reaching a short-term peak value. The reason for this overspecialization-induced decline can be deduced from Figure 4b, c. Figure 4b shows the embeddedness of team members 1 and 2. (The other team members' embeddedness is qualitatively similar but suppressed for clarity.) In contrast, Figure 4c shows the individual knowledge for team members 1 and 2 (again qualitatively similar to the other team members'). At the beginning of the simulation, both embeddedness and individual knowledge increase as expected, with the increases in both stocks reinforcing each other. However, as individual knowledge increases, it begins to activate the balancing loop B3 shown in Figure 2. This loop decreases the ability of team members to communicate, which in turn reduces how quickly tie strength accumulates due to an increased number of tasks completed. After a delay that depends on the team member, the effects of this balancing loop become so strong that the increase in tie strength from task completion no longer exceeds that lost to tie depreciation. Thus

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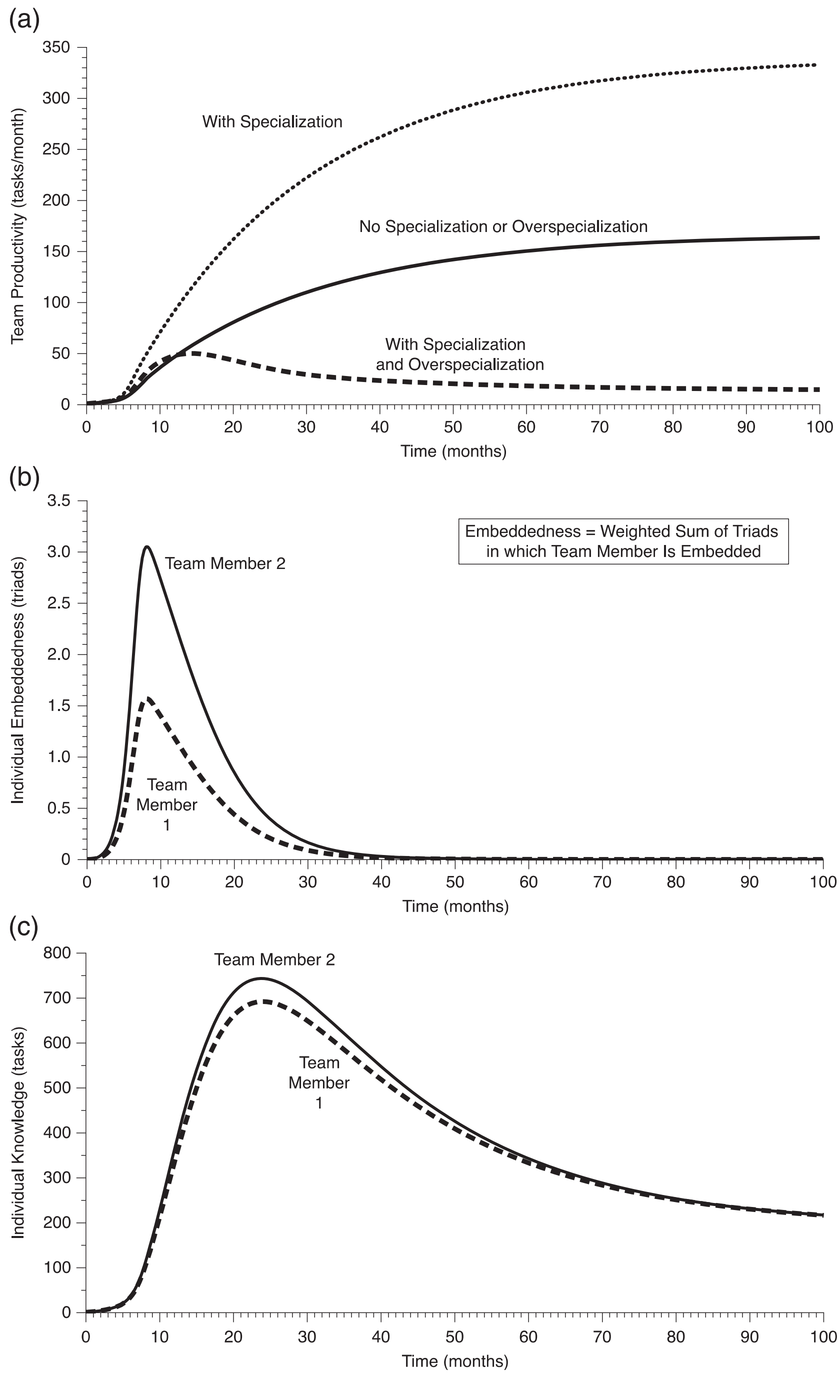

Fig. 4. (a) Effects of specialization and overspecialization on team performance. (b) Individual embeddedness for team members 1 and 2 in Case 3. (c) Individual knowledge for team members 1 and 2 in Case 3

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embeddedness actually begins to decline, turning the reinforcing loop R1 in Figure 2 from a virtuous (reinforcing beneficially) into a vicious cycle (reinforcing detrimentally). Even so, for a while, individual knowledge still increases sufficiently to offset the decline in embeddedness. As the increase in individual knowledge begins to slow, however, it can no longer offset the decrease in embeddedness, which causes the task completion rate to begin to drop in month 13. This in turn causes the increase in individual learning to slow even faster. Finally, between months 20 and 25 (depending on the team member), individual knowledge falls below the individual knowledge depreciation rate, causing individual knowledge to begin to decline. This drives reinforcing loop R2 also to change from a virtuous to a vicious cycle. Now both reinforcing loops are driving a decline in the task completion rate through the end of the simulation. These effects, while more nuanced than those explicated in Anderson and Lewis (2014), are similar. Specifically, the hybrid model specification of both individual and collective knowledge produces results that are consistent with past research, providing a robustness check on the model and addressing our first research question.

The effects of communication patterns and subgroup structures

We address the second and third research questions by modeling the effects of the communication network structure and diversity-based subgroups on learning and productivity. Anderson and Lewis (2014), because of their aggregate representation of collective knowledge, assumed that all individuals were homogeneous. Of course, in reality, this is not typically the case. Returning to the robotics team, assume that the individuals of this team are heterogeneous on some dimension, such that individuals could be *perceived* to be members of different subgroups defined by difference on this dimension. The particular dimension on which members differ can be somewhat arbitrary (e.g., gender, expertise (function, department), generational “age”, educational background), as long as members perceive that members differ along that dimension. For the purposes of illustration, we suppose that the engineers differ in terms of their educational backgrounds—with some engineers having an engineering degree from Georgia Tech (GT) and others having an engineering degree from Massachusetts Institute of Technology (MIT). Assume that each of the seven members of the team belongs either to the GT or the MIT subgroup. The two subgroups could be perceived as different, based on assumed differences in curricula. As an example, for illustrative purposes only, GT engineers may have relatively better knowledge of how to manage hardware projects in the real world, having had cooperative (CO-OP) experience during their education, whereas MIT engineers may be especially skilled at the theoretical underpinnings of robotic movement (e.g., servomechanism control). This gives the two subgroups different bases of knowledge, thus hindering easy communication between them. A member

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in one subgroup may not understand a member in the other subgroup as easily as one who is in the same subgroup, per the diversity literature cited above.

We examine the implications of this type of team diversity by hypothesizing that (i) members of different subgroups will, *ceteris paribus*, communicate less with each other, thus hindering the formation of ties between the two, and (ii) teams with greater diversity overall will contain a greater variety of skill sets, facilitating more rapid member specialization than those teams with less diversity. This latter point is supported by empirical findings, including Lewis (2004), who found that members of consulting teams who were aware of other members' different functional expertise a priori were more likely to develop a TMS and leverage the TMS for higher team performance. In contrast, in teams where members' functional expertise was less apparent, members took longer to develop the division of cognitive labor (specializations) that is characteristic of a TMS—presumably because learning about others' actual expertise takes some time.

To operationalize the two hypotheses just described, let.

$\mathbf{s^i}$ = a vector of dimension N, which describes the subgroup to which a team member belongs. While this could be any number of subgroups, we will only model two. If $s_j^i = 1$, then individual j is of the GT subgroup; else, if $s_j^i = 0$, the individual is of the MIT subgroup;

ψ = reduction in tie accumulation between two team members if there is a subgroup mismatch.

If two members are of the same subgroup, i.e., $s_j^i = s_k^i$, then there is no effect on tie strengthening rate in Eq. (4b). If they are, however, of different subgroups, i.e., $s_j^i \neq s_k^i$, then we reduce the dyadic tie strengthening rate. Thus we rewrite Eq. (4b) in the simplest form possible, a linear function, to capture these two effects:

$$\frac{\mathrm{d}A_{j,k}(t)}{\mathrm{d}t} = p(t)S\left(s_j^i, s_k^i\right)H_{j,k}^a(t)C_{j,k}^a(t) - \chi^a\left[A_{j,k}(t) - A_{j,k}(0)\right] \text{ for all } j \in \{1 \ldots N\} \tag{4c}$$

where the mismatch function $S\left(s_j^i, s_k^i\right)$ is defined: $S\left(s_j^i, s_k^i\right) = 1$ if $s_j^i = s_k^i$, else $S\left(s_j^i, s_k^i\right) = \psi$ where $0 \leq \psi < 1$.

We now model the impact of diversity on the effect of specialization. Empirical research on TMS suggests that diversity allows rapid specialization (Lewis, 2004) but weakens ties between people who are perceived as different (Gibson and Vermeulen, 2003). In our example, a team with a member experienced in project management such as the GT alumni will be able to specialize in project management more effectively than if the team

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members all graduated from MIT. Using D to represent the effect of this diversity, we represent this by rewriting Eq. (11) as

$$g\left[k_j^a(t)\right] = D\left(\mathbf{s}^i\right)\left(1+\frac{k_j^a(t)}{k^{a^*}}\right)^{\sigma} \text{ for all } j \in \{1..N\} \text{ such that } 0 \leq \sigma < 1 \tag{11b}$$

where

D = the effect of diversity on specialization, which is modeled as

$$D\left(\mathbf{s}^{\mathrm{i}}\right) = D_{\min} + \left(1 - D_{\min}\right)\left\{\frac{1}{N}\left[N - \max\left(\sum_{j=1}^{N} s^i(j), N - \sum_{j=1}^{N} s^i(j)\right)\right]\right\} \tag{13}$$

for $j \in \{1..N\}$ and where $0 \leq D_{\min} < 1$.

$D(\mathbf{s}^{\mathrm{i}})$ is a function lying on the interval [0, 1] that represents the diversity in terms of subgroup membership of team members. If all members come from a single subgroup (i.e., all team members are GT alumni), then the ability for the team to specialize will be most hindered, and $D(\mathbf{s}^{\mathrm{i}})$ will drop to its minimum value $D_{\min}$. For the robotics team example, we assume there are three team members from GT and four from MIT in a team of seven in total. This represents a moderately diverse team with two similarly sized subgroups, wherein specialization will become relatively easy, making $D(\mathbf{s}^{\mathrm{i}})$ rise. If there were many more than the two subgroups in this paper, $D(\mathbf{s}^{\mathrm{i}})$, slightly modified to capture the size of the largest subgroup, would approach the maximum of one. In more imbalanced subgroups, such as a team divided into a two-person GT subgroup and a five-person MIT subgroup, $D(\mathbf{s}^{\mathrm{i}})$ will decline, because the size of the larger group declines (hence, the "max" in the function above). Because the effect of diversity results from an aggregation of individual ties, it is essentially the effect of an SFM-like construct, $D(\mathbf{s}^{\mathrm{i}})$, on an ABM-like construct, $g_j^i(t)$.

Comparing diversity effects

Now we make an initial test to determine whether the model can capture the effects of teams composed of members who differ in terms of their educational background. We examine one homogeneous scenario (Scenario 1), in which members are similar, and three "diversity" scenarios (Scenarios 2, 3 and 4) that vary in terms of members' positions in the communication network. The model scenarios are depicted in Figure 5, which shows the different structural position(s) of GT engineers (shaded circles) and MIT engineers (white circles) that are possible assuming the seven-member hierarchy in Figure 3. For ease of exposition, we describe members with direct links to other members at a *lower* level of the hierarchy as *managers*; we remind readers that the hierarchical structure as used in this paper only reflects

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patterns of communication rather than power differentials or decision rights. Scenario 1, in which all members are similar, is akin to Anderson and Lewis (2014). In Scenario 2, three manager positions in the hierarchy are held by GT graduates (shaded), while the four non-manager positions are held by MIT graduates (white). Scenario 3 describes a team in which all members from GT are positioned in a lower-level subhierarchy, and MIT members are positioned elsewhere. Finally, Scenario 4 describes a team in which the top-level manager is from GT, mid-level managers are from MIT, and the remaining GT and MIT members are dispersed subhierarchies. Note that the number of members from each of the two diversity-based subgroups are identical for Scenarios 2, 3 and 4 with three “GT” and four “MIT” members each.

To show how this model can be used to illustrate the interplay between hierarchical relationships and diversity-based subgroups, we begin by contrasting the simulated productivity of a homogeneous team (Scenario 1—all GT members), with that of the more diverse Scenario 2 (GT managers).

Contrasting Scenario 1 (homogeneous team) with Scenario 2 (GT managers)

Figure 6a–c represents, respectively, team productivity, average contribution from individual knowledge, and average contribution from individual embeddedness as they evolve over the simulation. (The parameters of these simulations are the base parameters for the rest of the paper.) The diversity represented in Scenario 2 (GT managers) allows the team to rapidly specialize, increasing each member’s individual productivity, thus raising team performance. In contrast, the homogeneous team represented in Scenario 1 begins to lag behind in its performance, because it lacks diversity, hindering members’ ability to specialize.

Over time, the team in Scenario 2 begins to overspecialize. A pattern similar to that discussed in Figure 4 follows. The individual team members communicate less with each other, progressively weakening their network ties, which in turn drives down each member’s individual embeddedness in the communication network. After month 21, the average contribution of each team member’s individual embeddedness has weakened so much that the

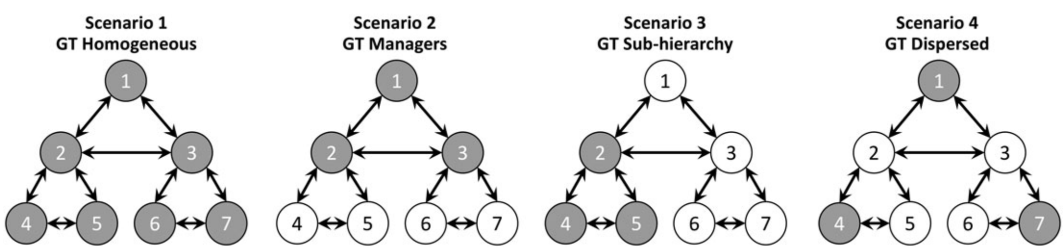

Fig. 5. Subgroup memberships for each scenario (GT team members’ nodes are shaded. MIT team members’ nodes are white)

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team cannot effectively leverage the individual productivities of other team members during the completion of tasks. Hence team performance as a whole begins to decline. As team performance declines, individual knowledge stocks cannot accumulate enough new knowledge to offset knowledge lost through depreciation, causing individual productivities to decline, slowing the team task completion rate (team productivity in Figure 6a) still further. As the task completion rate declines, so too do the accumulations of both individual knowledge and network of tie strengths, driving the task completion rate down even further in a vicious cycle. Eventually, however, as individuals' knowledge stocks decline, so too do the negative effects of overspecialization. At approximately month 60, team members become able to strengthen ties again, increasing the contribution from team members' individual embeddedness. This allows the team to better leverage individual productivities, increasing their performance. Eventually even individual productivity begins to recover. However, overspecialization eventually occurs again, and by approximately month 85 the task completion rate begins to drop off again.

In contrast, the homogeneous team (Scenario 1) has less diversity to exploit, which hinders specialization. Instead, the team must rely on stronger ties to increase the embeddedness of team members, which gives the team enough of a TMS to leverage what little specialization members can develop. Hence, in comparison with Scenario 2 (GT managers), the growth in the task completion rate in Scenario 1 is due to a stronger TMS than it is to individual specialization. The growth in performance takes longer in Scenario 1, which is why the team's performance only begins to catch up with the Scenario 2 team at month 33. However, because specialization is delayed in Scenario 1 until after individual embeddedness is highly developed, individual productivity is less affected by overspecialization. Hence there is only an asymptotic approach to a maximum level of the task completion rate with no overshoot. Under different parameters (e.g., the point at which an individual becomes overspecialized k^{i*}), there could indeed also be an overshoot and collapse in Scenario 1 (as shown below, in sensitivity studies). But if so, that overshoot and collapse would occur later and be of less amplitude than in Scenario 2, because of the relatively stronger reliance on the team's TMS, relative to specialization. Thus there is a dynamic trade-off in which the team in Scenario 2 peaks earlier and the team in Scenario 1 peaks later. Hence the more diverse team in Scenario 2 produces team performance that is stronger relative to Scenario 1 in the short term, but relatively weaker in the long term.

Diversity scenarios: comparing scenarios 2, 3, 4

We next model the effects created by different forms of diversity-based subgroups. The same effects could be replicated with a traditional SFM model

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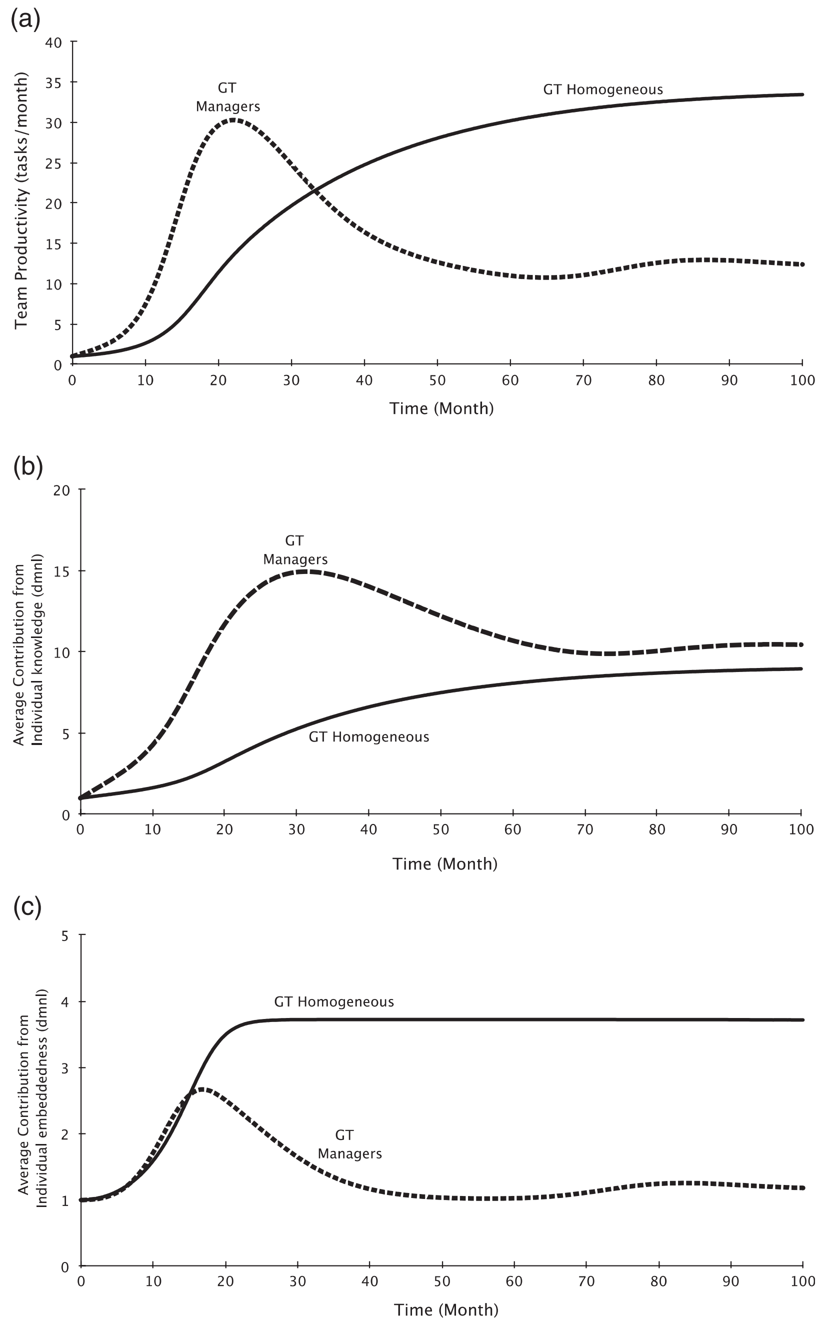
Fig. 6. (a) Performance for diverse versus homogeneous teams. This is the base scenario for the remainder of the paper. The parameters are in Table A1 in the Appendix. The differences between the homogeneous team (Scenario 1) above and the scenario in Case 3 shown in Figure 4 arise from the effect of diversity being absent in Figure 4's simulations. (b) Contribution from individual knowledge for Scenario 1 (GT homogeneous) versus Scenario 2 (GT managers). This represents only the average of the contribution of individual knowledge to team productivity for each scenario, which roughly indicates the contribution from each team member solely from their individual knowledge. Each team member's individual productivity will, of course, vary in magnitude, as well as be influenced by the individual embeddedness shown in the part (c) graph. (c) Average contribution from individual embeddedness for Scenario 1 (GT homogeneous) versus Scenario 2 (GT managers). This represents the average of team members' contribution from individual embeddedness for each scenario, which indicates the contribution from team members' individual embeddedness. Each team member's embeddedness will, of course, vary in magnitude, as well as be influenced by the individual productivity shown in the part (b) graph



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with one stock for individual knowledge and one for a collective TMS, as in Anderson and Lewis (2014)—the only difference being the addition of a diversity variable influencing the effect of TMS on specialization. This traditional approach, however, would make contrasting the diversity scenarios impossible, because in each scenario there are three GT members and four MIT members. The diversity variable in each of the different scenarios—the ratio of the two subgroups' members—would be identical. There would be no way to differentiate between the scenarios without creating a separate auxiliary variable that captures centrality or dispersion with some sort of index. Specifying the dynamic evolution over time in a realistic manner, while not impossible, would be much less straightforward than using a hybrid model, whose extensions added from ABM can directly capture individual properties and dyadic relationships. Doing so in this paper's model is, in contrast, straightforward, requiring only a change in the $\boldsymbol{s}^{\mathbf{i}}$ vector. This is crucial, because the different positions of members in Scenario 2 (GT managers), Scenario 3 (GT subhierarchy) and Scenario 4 (GT dispersed) matter significantly, as shown in Figure 7a, which compares the performance of all four scenarios' teams from Figure 5.

In Figure 7a–c, the behavior of the three diversity scenarios (2, 3 and 4) are markedly different, not only from the homogeneous case in Scenario 1 but also from each other. The three diversity scenarios begin similarly, with productivity growth that is more rapid than in Scenario 1, for reasons discussed above. However, the length and magnitude of their short-term productivity dominance over Scenario 1 differ. Scenario 3 (GT subhierarchy) attains the highest productivity of all scenarios at month 22, but then begins a long-term overspecialization-induced productivity decline with some oscillation characteristic of many real-world teams (Allen, 1977; Anderson and Lewis, 2014). This is due to the ability of the team's structure to create a high level of individual embeddedness, and hence TMS (Figure 7c). Higher individual embeddedness and TMS stimulate specialization to increase individual productivity (Figure 7b). However, the extremely high level of embeddedness begins to decline at month 15, because overspecialization affects tie accumulation by weakening ties or even retarding tie accumulation. These effects in turn weaken individual embeddedness, and hence TMS. Because the resulting weak TMS does not significantly throttle individual productivity, a new equilibrium (with only minor oscillations) is reached at month 70, which traps team productivity at a low level throughout the rest of the simulation. While Scenarios 2 and 4 do not reach the same peak performance as shown for Scenario 3, teams in Scenarios 2 and 4 also are trapped by the high individual productivity–low TMS equilibrium resulting from overspecialization, causing their performance to generally, though not exactly, converge by the end of the simulation.

Why is the behavior of the three diversity scenarios so different, particularly in terms of peak value and degree of productivity decline? *Crucially,*

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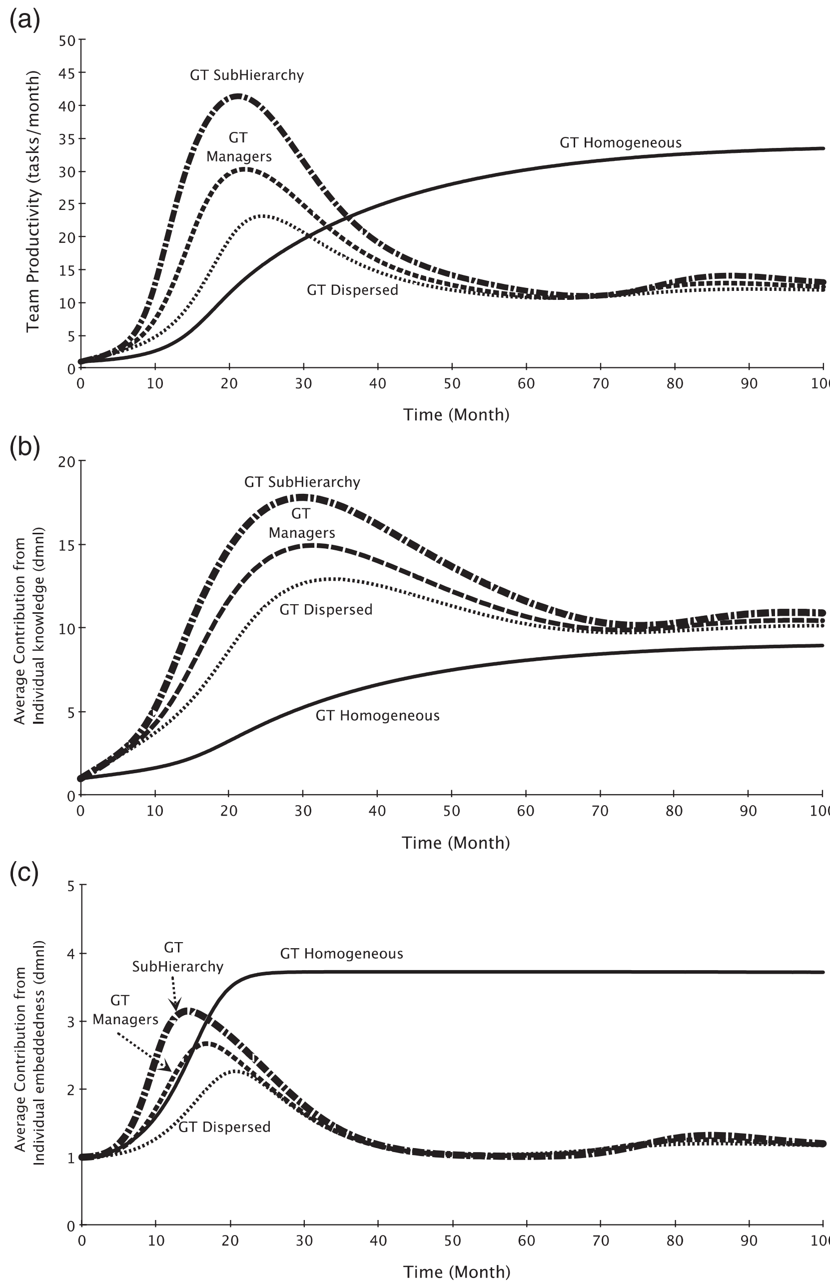
Fig. 7. (a) Performance of different scenarios. The parameters in this model are the same as those for Figure 6a–c, the values of which are in the Appendix. (b) Average contribution from individual knowledge of different scenarios. This represents only the average of the contribution of individual knowledge to team productivity for each scenario, which roughly indicates the contribution from each team member solely from their individual knowledge. Each team member's individual productivity will, of course, vary in magnitude, as well as be influenced by the individual embeddedness shown in the part (c) graph. (c) Average contribution from individual embeddedness for different scenarios. This represents the average of team members' contribution from individual embeddedness for each scenario, which roughly indicates the contribution from team members' individual embeddedness. Each team member's embeddedness will, of course, vary in magnitude, as well as be influenced by the individual productivity shown in the part (b) graph



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the differences among the productivities of the diversity scenarios is not due to the number of members from each subgroup, which is constant among the three scenarios. Rather it is from members' positions in the communications hierarchy.

These results support the view that clustering "similar" members together in a subgroup is more effective than dispersing them. This result stems from the number of transitive triads among team members from the same subgroup in each scenario's indicated network. Given the model's continuous formulation, all team members will be embedded in transitive triads and hence be embedded within the team's communication network to some degree. However, a team member's embeddedness varies with her position within the indicated network, *which the hybrid model formulations allow us to capture.* Individual embeddedness resulting from homogeneous subhierarchies is in general stronger than in more diverse subhierarchies, thus affecting the resulting TMS differently. Moreover, Scenario 3 (GT subhierarchy) has stronger individual embeddedness (Figure 7c) because all members in one subhierarchy are from MIT and, in the other, all members are from GT. The resulting TMS leverages members' diverse strengths particularly effectively. In contrast, Scenario 4 has no transitive triads composed of "similar" subgroup team members in its indicated network, resulting in weaker individual embeddedness and thus a weaker TMS. Hence a team in Scenario 4 cannot exploit diversity to specialize its team members nearly so well as a team in Scenario 3. However, the increased embeddedness of members in Scenario 3, because embeddedness can so strongly stimulate specialization, makes the team more prone to damage from overspecialization. Hence Scenario 3's collapse is much more spectacular than is Scenario 4's. Finally, Scenario 2 is an intermediate case, in terms of the number of transitive triads of similar team members in its indicated network. Hence its peak and collapse are intermediate as well.

These results support that overlap in diversity-based subgroups and members' positions in the communication network does not produce the negative effects predicted by much of faultline literature. Instead, our results support the alternative view, that clustering "similar" members into subgroups is better for team performance. Our simulations suggest that dispersing members (and thereby dismantling a faultline) does not improve team performance; instead, higher team productivity emerges when team members from the same subgroup are clustered together.

Sensitivity analyses

A range of sensitivity studies for the proposed model are presented in the Appendix. In this section, we discuss only the most important results. In

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particular, under sensitivity analyses, several results from the base simulations remain robust. Performance in the homogeneous scenario (Scenario 1) always peaks later than in the three diversity scenarios, and any subsequent collapse (which does occur under some parameters) is less severe in the homogeneous scenario. The reason is that the homogeneous scenario's performance is always more dependent on accumulating tie strength and is less prone to overspecialization than are the diversity scenarios. Among the diversity scenarios, the peak performance of scenario 3 (GT subhierarchy) is always higher than in Scenario 2 (GT managers), which in turn is higher than in Scenario 4 (GT dispersed). This ordering results from Scenario 3's increased clustering of members from the same subgroup over Scenario 2, which in turn is more clustered than is Scenario 4.

There are also differential effects. There are two of particular import. One is that parameter changes that increase the effect of individual knowledge on productivity generally favor performance in the diversity scenarios over the homogeneous scenario. The reason again is that the diversity scenarios are more dependent on specialization, while the homogeneous scenario is more dependent on accumulating tie strength. For the same reason, parameter changes that increase the effect of embeddedness on productivity generally favor performance in the homogeneous scenario.

Dichotomous ties

As a final sensitivity test of the model, we test the importance of continuous measures of tie strength resulting from our SFM-like formulations, given that in many SNA models ties are represented as dichotomous. To simulate the effects of dichotomous ties on the model, we modify Eq. (5). Let

$$f\left(A_{j,k}, A^{*}\right) = 1 \text{ if } A^{n}{}_{j,k} \geq A^{*}; 0 \text{ if otherwise for all } j,k \in \{1 \ldots N\} \tag{5b}$$

The results in Figure 8 are the result of dichotomous ties resulting from substituting Eq. (5b) for Eq. (5) in the base model. No other changes are made. Clearly, the results are much harder to interpret than in the base model, which has continuous ties, as shown in Figure 7a. This result shows the importance of using continuous ties, as is typical of SFM (and often ABM) when modeling team processes and performance.

Discussion, limitations and conclusion

The goal of this paper was to demonstrate the usefulness of combining aspects of stock-and-flow models, agent-based models and social network analysis in investigating the dynamic behavior of small teams. To this end,

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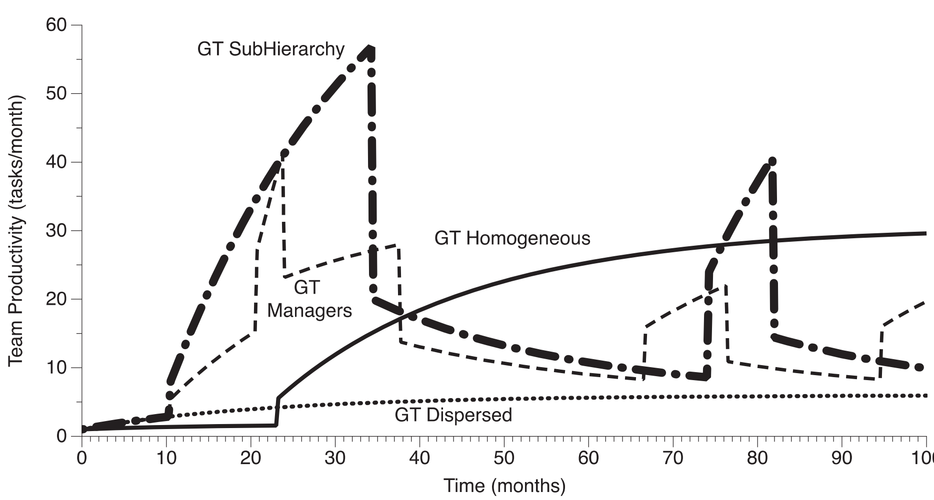
we first discussed the potential advantages of combining them to specify formal mathematical models to study issues of complex dynamic behavior resulting from the network of ties in teams. This approach enabled us to build a model examining areas of research interest for team science. Team science methods are particularly challenging because of the need to simultaneously consider individual member capabilities, emergent relationships among team members and multiple feedback loops among multiple levels of analysis (e.g., individuals, dyads and team levels). We applied aspects of agent-based modeling techniques, including individual heterogeneous attributes, with those of social network analysis, emphasizing disaggregated dyadic relationships, into a stock-and-flow framework, with accumulation and feedback structures.

We then examined at length an important set of questions in team science, relating individual member attributes to team emergent processes and structures. We examined three research questions in a proof-of-concept model. Simulations using the model confirmed previous findings from Anderson and Lewis (2014) that there can be an overshoot and collapse in team performance. We also found support for the conjecture that productivity of diverse teams is often higher than that of homogeneous teams (van Knippenberg and Schippers, 2007). Two important novel implications for theory resulted from this study. First, the finding that teams in the diversity scenarios outperform the homogeneous scenario is temporally nuanced. Our model suggests a short versus long-term tradeoff of diversity on team performance. Diverse teams were found to be better for short-term tasks because they can quickly exploit diversity to specialize. However, homogeneous teams may be relatively better for long-term tasks because they can, over time, better accumulate dyadic ties within the team—thus

Fig. 8. The effect of dichotomous ties on team performance



building a strong TMS—and because homogeneous teams are less prone to overspecialization. Moreover, homogeneous teams are less prone to the overshoot and collapse behavior in team performance than are diverse teams. The implication for management is that diverse groups may be relatively better for short-run projects, while homogeneous groups may be better for long-term projects.

Second, the peak performance resulting from different arrangements of diverse teams' subgroup membership can be differentially effective in the short term. In particular, our model provides support for the view that higher peak team productivity results from teams whose members are clustered by subgroup rather than dispersing members from different subgroups evenly throughout the team. This means that using dispersion as a tool to improve team productivity is contraindicated. However, temporal nuance is also important to the behavior of diverse teams. While different configurations of subgroup team members create differential performance in the short run, all configurations tend to experience some sort of overshoot and collapse behavior. This results in a long-term convergence in team performance. Management might be better served, at least in the short run, by clustering team members of the same subgroups rather than dispersing them evenly throughout a team.

There are limitations to this hybrid modeling approach. First, the model is a simulation and the results stem from simulation runs. While the dynamic behavior of the model is theoretically novel and difficult to intuit beforehand, the model still has the same weaknesses as do all simulation models. Firstly, the results of this study are contingent on the parameters characterizing the system in which the team operates. For example, the sensitivity studies show that, as team productivity becomes more dependent upon individual learning rather than a strong network of interpersonal ties, the more likely it is that the performance of diverse teams will dominate that of homogeneous teams in both the short and long run. As another example, the short-run advantage of clustering members from the same subgroup in diverse teams increases with the difficulty of building ties between members of different subgroups. There are also the other issues typical of simulation studies *vis à vis* their empirical counterparts. From a team science standpoint, there are potential explanatory factors missing. For example, the dynamic network of ties could also incorporate relations other than communication, such as friendships, business transactions, etc. This would make the model's network multiplex as well as multilevel and thus truly multidimensional (Contractor *et al.*, 2011). Similarly, incorporating technologies and tasks into the team network structure could be instructive (McGrath and Argote, 2001). Another potential area of inquiry would be to scale up from teams to arbitrarily larger units, such as, divisions and firms per Argote (1999). These would all make excellent extensions for future research. That said, applying formal modeling to team science using a hybrid approach as

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presented in this paper might be a valuable base on which to build, while pursuing these lines of inquiry.

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Notes

[i]The initial input to the dynamic model is a network of relationships between individuals (Indicated Network Structure). We note that the network could additionally represent relationships between people, tools or sub-tasks. Moreover, this initial network could be defined by existing or new empirical research, or it can be deliberately manipulated to represent certain structures of interest. For example, the network could represent other ongoing relationships such as telephone or email contact (Freeman, 2004), collaborative tools (supply chain relationships (Bellamy and Basole, 2013) or a whole host of cognitive relations (such as "knows" or "views as similar"), affective relations (such as "likes" or "respects"), actions (such as "meets with" or "attacks"), co-occurrence (representing "same demographic characteristic" or "affiliated with the same organization"), etc. (Wasserman and Faust, 1994). For the purposes of this paper, the network represents the formal and informal communication patterns among team members.

[ii]For simplicity, we follow Anderson and Parker (2002) by assuming, quite plausibly as we are considering team formation, that team members start without any prior ties to other members by setting the minimum tie strength equal to that of its initial value. However, the two constructs can be easily separated into two variables in a straightforward manner if so desired. Also, it is important to note that we have restricted $C^{a}(j,k)$ to have values of 0 or 1 for simplicity. Importantly, if the value is zero, no tie will develop between team members j and k beyond the minimum level in $A(0)$. However, sensitivity testing has shown that for intermediate values rather than zero the qualitative results of this paper are robust to this assumption over a wide range of parameters.

[iii]For the economic production function that is team productivity, we use the average of individual production functions following separability inherent in Reagans *et al.* (2005) rather than a Cobb–Douglas, constant elasticity of substitution (CES) or Leontief function. A Cobb–Douglas or CES formulation is highly complex. A Leontief function, because it clips productivity to the productivity of the lowest team member, is clearly unrealistic. In our robotics team example, for instance, a team with a "rookie" would be constrained to that rookie's productivity using this formulation, but in reality such a team would likely work around the rookie's lower productivity

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to—at least partially—sustain team performance. Despite the linear formulation chosen, the individual productivities vary in a nonlinear way because of the power law formulations in Eqs (2) and (8). Hence averaging them at a team member level captures dynamics that would be impossible using aggregate stocks of team experience and team TMS, as demonstrated explicitly in the section titled "The effects of communication patterns and subgroup structures".

Biographies

Edward G. Anderson Jr. is Wright Centennial Professor for Management of Innovative Technology at the University of Texas McCombs School of Business. He received his bachelor's degree from Stanford University and his Ph. D. from the Massachusetts Institute of Technology. His research and practices center on distributed innovation management and performance improvement, particularly in the contexts of digital platforms and healthcare. Anderson is a Fellow of the Production and Operations Management Society, and he has received the Jay Wright Forrester Award for his work on performance improvement. He holds six patents. His research has been funded by the National Science Foundation and the Veterans Administration. He is department editor of the Industry Studies & Public Policy Department of *Production and Operations Management* journal.

Kyle Lewis is the Chair and Professor of Technology Management at UC Santa Barbara. She received her bachelor's degree from Duke University, an M.S. from Carnegie-Mellon University, and a Ph.D. from the University of Maryland. Her research examines how organizations leverage individual and collective knowledge and how this knowledge affects the performance of teams, especially those teams engaged in knowledge work such as professional services, new product development, and project-based tasks. Among other awards, she has received the Jay Wright Forrester Award for her work on performance improvement.

Gorkem Turgut "G.T." Ozer is an Assistant Professor in the Decision, Operations, and Information Technologies Department at the Robert H. Smith School of Business, University of Maryland, College Park. He received his Ph.D. from the McCombs School of Business, University of Texas at Austin. His research and practice lie at the nexus of technology, strategy, and organization, and involve large scale data analysis using statistical models and machine learning algorithms. G.T. is also an award-winning teacher and advisor on data centricity, big data, and artificial intelligence strategy.

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APPENDIX

Base parameter values

Table A1 Parameter values for model

γ^i	Individual productivity power law parameter	0.5 dmnl*
γ^a	Individual embeddedness power law parameter	0.7 dmnl
$1/\chi^i$	Individual knowledge depreciation time	12 months
$1/\chi^a$	Tie strength depreciation time	12 months
$k^i(0)$	Initial individual knowledge and also reference knowledge units for power law function	1 task
k^{a*}	Reference tertii for normalization in power law function	0.5 tertii
$A(0)$	Initial tie strength	1 if in formal network; 0 otherwise
$A*$	Reference value to normalize strength of a tie	30 tasks
σ	Specialization parameter	0.25 dmnl
k^{a*}	Reference tertii for specialization	2.5 tertii
ω	Overspecialization parameter	5 dmnl
$k_1^{i^*}$, $k_2^{i^*}$	Reference individual knowledge for overspecialization	150 tasks for both
$D_{\min}$	Minimum value of $D(s^i)$, which is the effect of diversity on specialization	0.1 dmnl
ψ	Subgroup mismatch penalty	0.25 dmnl
C^{a*}	Value of $C^a(t)$ if there is a formal connection in the indicated network structure. This value is used for normalization for comparison with other indicated network structures not used in this paper	2.33 dmnl

*dmnl is an abbreviation for dimensionless.

High-level sensitivity analyses

Results common to all sensitivity tests

Under all sensitivity tests, several results remain qualitatively robust. First, for the diverse teams represented in Scenarios 2, 3 and 4, Scenario 3's (GT subhierarchy) peak performance is always higher than in Scenario 2 (GT managers), which is in turn always higher than Scenario 4 (GT dispersed). This ordering is due to the effect of tie formation among

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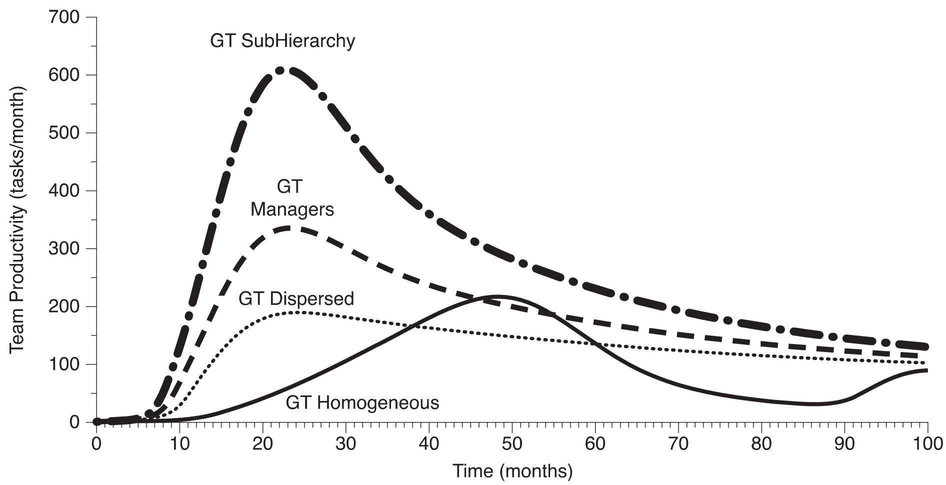
Fig. A1 Team performance when the individual learning curve parameter γ^i is increased. Note that the *x*-axis scale differs in Figures 7a, 9 and 10 to avoid readability problems due to the nonlinear results arising from changing power law parameters



similar team members, due to the relative strengthening of TMS, as discussed previously.

Second, the differential in the three diversity scenarios occurs early. In the latter parts of all sensitivity runs, so long as there is overspecialization and knowledge depreciation the performances in Scenario 2, 3 and 4 all decline after their peak and converge to different, but similar, values.

Third, the peak performances in the diversity scenarios occur earlier than in Scenario 1 (homogeneous). One reason for this is that the effect of diversity on specialization is immediate in the diversity scenarios relative to the homogeneous case. Another reason is that diversity hinders accumulating tie strength between team members to develop an effective TMS, upon which the homogeneous scenario relies more heavily than the diversity scenarios.

Fourth, any long-run collapse of team productivity created by overspecialization in Scenario 1 (homogeneous) is less pronounced than in the three diversity scenarios. Because diversity does not promote immediate specialization in the homogeneous scenario, its team productivity relies relatively more on accumulating tie strength and is less prone to overspecialization.

Differential effects

When parameters are varied, there are often differential effects among the scenarios. An increase in any parameter that strengthens the individual learning curve, such as the individual productivity learning parameter γ^i, increases the peak team productivity of the diversity scenarios relative to the homogeneous scenario. This can be seen in Figure A1, in which γ^i is raised from the base case 0.5 (shown in Figure 7a) to 0.7. (Note that the *x*-axis scale differs in Figures 7a, 9 and 10 to avoid readability problems due to the

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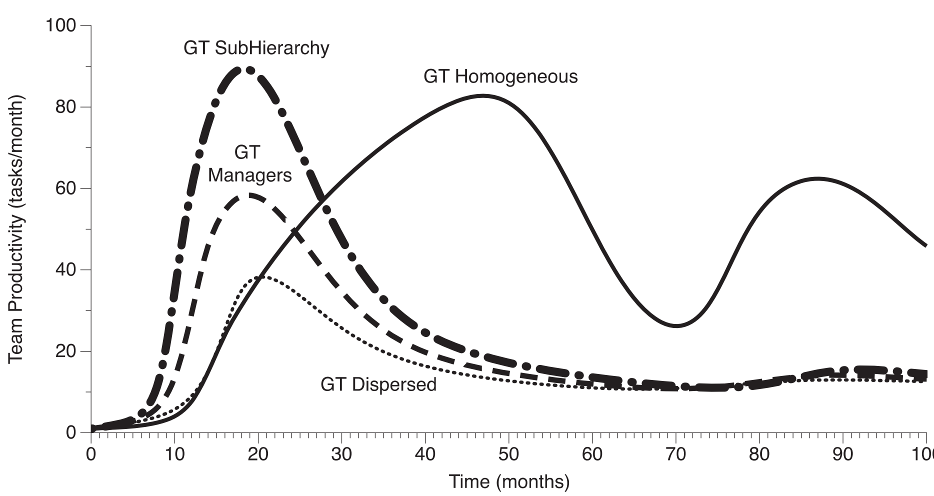
nonlinear results arising from changing power law parameters.) The reason is that the diversity scenarios rely relatively more on diversity to amplify the effects of specialization on team performance. The homogeneous scenario must instead rely more on accumulating tie strength to develop a strong TMS. This makes the homogeneous scenario's peak relatively less sensitive to an increase in the individual learning curve. That said, the homogeneous scenario is still somewhat dependent on individual productivity, which results in some increase in team performance. More interestingly, the homogeneous scenario's team members can now develop enough individual productivity that the team members can overspecialize and thus overshoot and collapse, though this is less pronounced than in any of the diversity scenarios.

In direct contrast, as the effect of the individual embeddedness increases, such as by increasing the embeddedness power law parameter γ^{α}, so too does the homogeneous scenario's peak team performance increase relative to the diversity scenarios'. (See Figure A2, which raises γ^{a} from 0.7 in the base case to 1.0.) Again, the reason is that the homogeneous scenario's team productivity relies relatively more on its accumulated tie strengths. The homogeneous scenario's team productivity begins to oscillate, much like that for stronger individual learning curves, as shown in Figure A1. However, the reason is different. The effect of TMS is indeed stronger relative to that of individual knowledge in Figure A2 than in Figure A1. As a result, the homogeneous scenario's team performance increases to the point that individual knowledge, which accumulates in part as a function of team performance, becomes high enough to overspecialize. This leads to the collapse in the homogeneous scenario's team performance seen in Figure A2, although again less than that of the diversity scenarios.

Fig. A2 Team performance when the embeddedness power law parameter γ^{a} is raised



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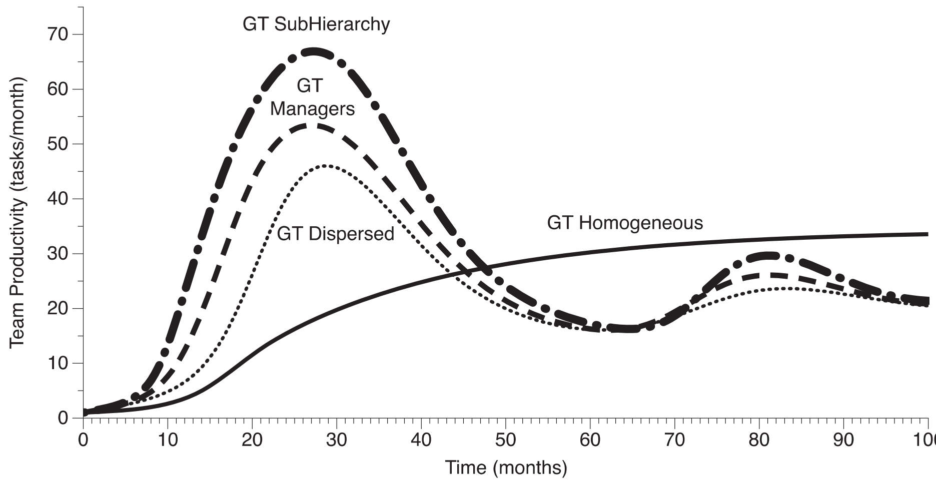

Fig. A3 Effect of increasing the reference individual knowledge at which overspecialization occurs

It is worth noting that oscillations exist in the homogeneous scenarios under both sensitivity tests that are absent in the base case as seen in Figure 7a. The driver behind these oscillations is different in both sensitivity tests, as previously described. However, a couple of points are common to both. One is that the response of team productivity to what seems to be a minor change in parametrization is quite drastic. This, however, is common in learning curves, because productivity follows a power law. As the power law parameter increases linearly, the resulting increase in productivity increases far more quickly than linearly. Moreover, because the model is a hybrid, individual characteristics exacerbate these tendencies. For example, the power law ensures that some individuals, such as those who are highly embedded, contribute disproportionately to team productivity. This causes the team productivity to be higher than would be the case in a pure SFM model, which represents embeddedness as an average aggregate. The aggregation, in turn, loses the impact of having individuals who disproportionately contribute. (This behavior is commonly referred to in mathematics as Jensen's Inequality.)

Additional sensitivity analyses

The main results of the sensitivity studies are presented in Table A2. Some particularly interesting generalized results include the following.

- Given the prior discussion, anything that increases the level of individual knowledge at which overspecialization occurs, such as increasing the normalization constants for overspecialization $k_1^{i^*}, k_2^{i^*}$, should also increase the diversity scenarios' peak productivty relative to the homogeneous scenario. This is indeed the case, as shown in Figure A3, in which the two parameters are increased from the base case of 150 tasks to 300 tasks.

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Fig. A4 Effect of reducing the effect of diversity by increasing $D_{\min}$

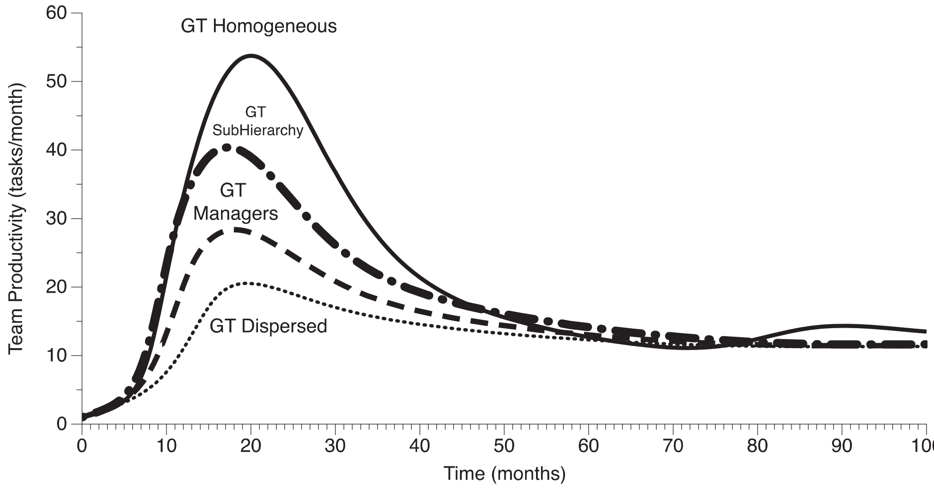
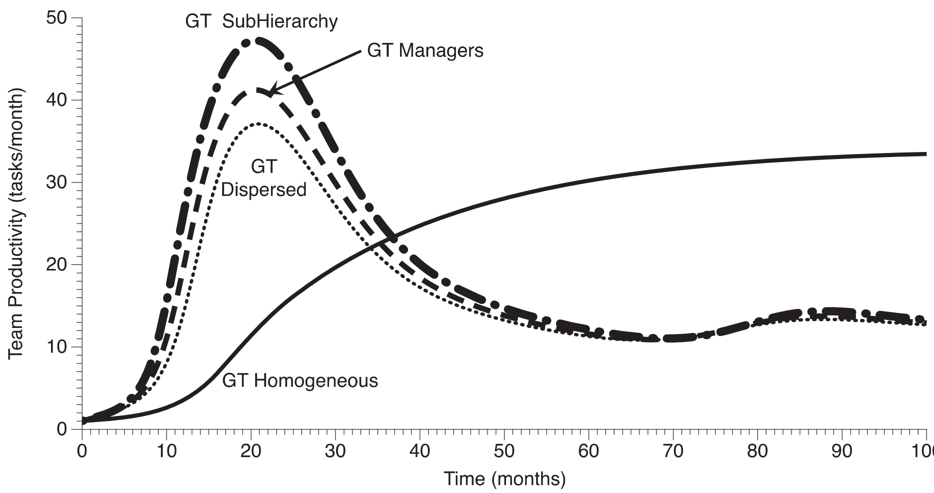


Fig. A5 Effect of reducing the penalty on subgroup mismatches for accumulating tie strengths



- Anything that increases the impact of diversity on specialization, such as raising $D_{\min}$, will (1) increase the homogeneous scenario's peak team productivity relative to the diversity scenarios' because diversity no longer boosts specialization; and (2) cause the peak of the homogeneous scenario's team productivity to occur earlier because the penalty for diversity is not as strong, so that it can leverage specialization earlier. However, this also increases the decline of the homogeneous team productivity because it is encountering overspecialization more quickly prior to developing a strong network of ties. These effects can all be seen in Figure A4, in which $D_{\min}$ is raised from 0.1 in the base case to 0.5. In effect, at this point the homogeneous scenario effectively mimics the diversity scenarios, except that its stronger network of ties, because it only has members of one subgroup, gives team productivity more of a boost at its peak. In contrast, reducing the effect of subgroup mismatches on accumulating tie strength ψ instead tends to cause the diversity scenarios' team productivities to converge, even in the short term. (See Figure A5, in which ψ is raised from its base of 0.25 to 0.5). The

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reason is that the penalty for accumulating ties is attenuated between the scenarios, so they become more similar. However, the homogeneous scenario's productivity is unaffected because it suffers no mismatch penalty.

Table A2 Sensitivity analysis parameter changes

Parameter	Effect on team productivity	Range
For all studies	**For diversity scenarios: the GT subhierarchy scenario's peak productivity is higher than the manager scenario's, which is in turn higher than the dispersed scenarios'. The peak for the diversity scenarios occurs earlier than for the homogeneous scenario. Also, the relative decline of the diversity scenarios' productivities after their peak will be greater than the homogeneous scenario's.**	
γ^i Individual productivity power law parameter	As parameter increases: **peak homogeneous team productivity *decreases* relative to the diversity scenarios, and diversity scenarios' peaks differ more from each other**. **All peak team productivities increase markedly**; peaks occur earlier, and the ratio of peak to decline is greater. For diversity scenarios, oscillation after the peak decreases, but for the homogeneous scenario it increases markedly.	0.3–0.7 dmnl*
γ^a Individual embeddedness power law parameter	As parameter increases: **the peak homogeneous team productivity *increases* relative to the diversity scenarios', and the diversity scenarios' peak magnitudes differ more from each other.** All peak team productivities increase; peaks occur earlier; oscillation increases (particularly for homogeneous scenario); and the ratio of peak to decline is greater.	0.4–1 dmnl
$1/\chi^i$, $1/\chi^a$ Knowledge and tie depreciation times (they are kept equal in this simulation study)	As parameter increases: peak homogeneous scenario productivity increases relative to the diversity scenarios', but the diversity scenarios' relative magnitudes remain similar. **All peak team productivities increase**; peaks occur earlier, and the ratio of peak to decline is greater. **For diversity scenarios, a marked oscillation at low values of depreciation time decreases**. For the homogeneous scenario, overshoot and decline appear for high values of depreciation.	6–24 months
$k^i(0)$ Reference individual knowledge for power law curve	As parameter increases: all peak team productivities drop; peaks occur later; and the ratio of peak to decline is less. For diversity scenarios, oscillation increases, but for the homogeneous scenario, decreases; **diversity and homogeneous peaks are closest for intermediate values.**	0.5–4 tasks
k^{a^*} Reference tertii knowledge for power law curve	As parameter increases: **peak diversity scenarios' productivities *decreases* relative to the homogeneous scenario**; all peak team productivities drop; peaks occur later; and ratio of peak to decline is less. For diversity scenarios, oscillation increases slightly, but for the homogeneous scenario, decreases drastically.	0.2–1 tertii
A^* Reference value to normalize strength of a tie	As parameter increases: **peak homogeneous scenario productivity *increases* relative to the diversity scenarios' and eventually overtakes them.** All peak team productivities drop; peaks occur later; and the ratio of peak to decline is less. For diversity scenarios, oscillation decreases. **Homogeneous scenario shows more of an S-curve.**	15–60 tasks

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Table A2. Continued

Parameter	Effect on team productivity	Range
σ Specialization parameter	Effects are almost negligible, other than increasing parameter values lead to very minor increases in oscillation for diversity scenarios. Also, there is a very minor overshoot and collapse in the homogeneous scenario for low parameter values.	0.12–0.5 dmnl
k^{a^*} Normalization parameter for specialization	Effect is almost negligible. There is a minor overshoot and collapse in diversity scenarios for low parameter values. Also, as the parameter increases, the peak homogeneous productivity declines very slightly relative to the diversity peaks.	1–5 tertii
ω Overspecialization parameter	There are only minor differences. As parameter increases: diversity scenarios' team productivities oscillate slightly less, and the peaks are slightly earlier. The homogeneous scenario becomes less S-shaped because its rise occurs earlier in the simulations.	2–10 dmnl
$k_1^{i^*}, k_2^{i^*}$ Normalization parameters for overspecialization (they are kept equal in this simulation study)	As parameter increases: **the peak homogeneous productivity magnitude starts higher than the heterogeneous scenarios' but *decreases* relative to them. Also, the diversity scenarios' magnitudes differ more from each other**. All peak team productivities increase and peaks occur later. For the diversity scenarios, oscillation increases significantly, but for the homogeneous scenario, significantly decreases. For diversity scenarios, the ratio of peak to decline increases, but for the homogeneous scenario, decreases.	75–300 tasks for both
$D_{\min}$ Minimum value of $D(s^i)$, which is the effect of diversity on specialization	**Generally speaking, as the parameter increases, the effect of diversity on specialization decreases and hence all the scenarios *look more similar*, including the homogeneous scenario**. For lower values, the homogeneous scenario differs from the diversity scenarios similarly to the other sensitivity studies above. In particular, as the parameter increases: **all diversity scenarios' team productivities remain relatively similar, except for the homogeneous scenario, which *increases* and overtakes them.** All peaks occur earlier (especially for the homogeneous scenario); and the ratio of peak to decline is greater, except for the homogeneous scenario, which increases. For diversity scenarios, oscillation increases slightly, but for the homogeneous scenario, significantly increases.	0.05–5 dmnl
ψ Subgroup mismatch penalty	For increasing parameter: **diversity scenarios converge**. It also slightly raises the diversity scenarios' team productivities relative to the homogeneous scenarios'. No change in the homogeneous scenario's team productivity.	0.1–0.5 dmnl

*dmnl is an abbreviation for dimensionless. Most significant effects are in **bold.**

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Table A3 Comparison of methods in a team science context

Comparison of methods in a team science context				
Methodological aspect	Stock-and-flow models (SFM)	Agent-based models (ABM)	Social network analysis (SNA)	Benefits of combining SFM, ABM and SNA in a team science context
Level of analysis modeled	Aggregate stocks (state variables)	Agents	Nodal-level interconnections	SNA interconnections and individual attributes (ABM) can be modeled simultaneously. Further, by using stock variables (SFM), both ties and individual attributes can accumulate, allowing the past to influence the future. Lastly, SFM enables representation of some aggregate values such as team performance. SFM also provides a library of well-defined formulations that can be used at the agent, as well as the aggregate, level.
System interactions emphasized	Dynamic behavior of high-level nonlinear feedback loops with delays between aggregate stocks	Nonlinear interactions of low-level agents	Network structure of ties (e.g., centrality, cliques, clustering)	SNA interdependencies and individual capabilities are represented at the team member level using ABM. Team aggregate state variables (SFM) can be *simultaneously* and *explicitly* modeled as well, allowing interaction between aggregate and agent-based constructs via feedback loops.
Relationships between entities	Equations to define relationships among aggregate variables (stocks)	Behavioral rules to define the ways agents interact with one another (e.g., simple rules)	Node-edge connections	Agent interactions can be defined at the agents' behavior level (ABM, SNA) when equations cannot be derived at an aggregate level (SFM) and vice-versa.
Time granularity	Continuous	Usually discrete	Mostly cross-sectional or longitudinal (multi-point)	A continuous (SFM)—or even sufficiently discrete (ABM)—model improves the pinpointing of tipping points and other dynamic phenomena for future empirical examination typically not done in classic SNA models.

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Table A3. Continued

Comparison of methods in a team science context				
Methodological aspect	Stock-and-flow models (SFM)	Agent-based models (ABM)	Social network analysis (SNA)	Benefits of combining SFM, ABM and SNA in a team science context
Correspondence to real-world variables	High	Low to high (extremely low for NK models)	Moderate to high (lower when dichotomizing ties)	Modeling organizational issues is facilitated by high levels of fidelity to real-world variables at the individual (e.g., generalist vs. specialist roles, ABM), collective (e.g., team, ABM/SFM) and system-wide (e.g., organizational learning, SFM; or clustering, SNA) levels.
Source of complexity	Nonlinear, system-level feedback and delays	Nonlinear interactions of numerous diverse agents	Network structure	Organizational and environmental complexity has aspects that can best be captured by examining both the high-level dynamic feedback dynamics of the system (SFM, e.g., effect of team productivity on tie strengthening) as well as those among its constituent agents (SNA/ABM, e.g., tie strength) and their properties (ABM, e.g., individual productivity).

Supporting information

Additional supporting information may be found in the online version of this article at the publisher's website.

Appendix S1. Online Vensim Model and Documentation.

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