Constructing the Team: The Antecedents and Effects of Membership Model Divergence

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2013/37/OB
(Revised version of 2012/94/OB)
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Revised version of 2012/94/OB
Draft – currently under review
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ABSTRACT

Scholars have established that team membership has wide-ranging effects on cognition, dynamics, processes and performance. Underlying that scholarship is the assumption that team membership – who is and who is not a team member – is straightforward, unambiguous and agreed upon by all members. Contrary to this assumption, I posit that mental models of membership increasingly diverge within teams as a result of changing environmental conditions. I build on the literatures on membership and on shared mental models to explore such “membership model divergence”. In a study of 38 formally defined software and product development teams, I test a model of structural and emergent drivers of membership model divergence, and examine its effect on performance operating through team-level cognition. I use the findings of this study to explore its implications for both management theory and managerial practice.

Keywords: Teams; Membership; Composition; Boundaries; Perception; Mental Models; Project-based Work
Abe – a member of “Alpha” product development team – sat frustrated as he read the onslaught of criticism from his teammates on a presentation he had recently made to the board on their behalf. The board had turned down Alpha’s new project, and his teammates were calling his presentation incomplete and off-target, and claiming he had ignored some of their most important arguments. This bewildered Abe as he had met with each member of the team individually the previous week, asking for comments on his draft. Betty explained that Abe hadn’t included any of the arguments Chris and Denise had made. Why should I? thought Abe. Chris and Denise are not even on the team.

This scenario illustrates a phenomenon that I refer to as membership model divergence and define as misalignment among team members’ models of who are, and who are not, team members. I argue that agreement on team membership is often implicitly assumed in both theory and practice, but that such an assumption is increasingly inaccurate given the changing nature of work and teams. Indeed research suggests that teams that are increasingly dynamic (e.g. Edmondson 2012; Hackman and Wageman 2005; Prencipe and Tell 2001), heavily interlinked or overlapping (e.g. Ancona and Bresman 2007; Matthews et al. 2011; O’Leary et al. 2011a), globally dispersed (Gibson and Gibbs 2006; Maznevski and Chudoba 2000; Schiller and Mandviwalla 2007), or any combination thereof. It has been argued that such shifts require a reassessment of how we think of and approach teams (e.g. Hackman and Katz 2010; Mortensen 2012; Oldham and Hackman 2010) and in all cases stand to increase divergence of membership models, as in the scenario above.

With this paper, I seek to accomplish three things. First, I draw upon existing theory and research on shared mental models to define membership model divergence. Second, I conduct an empirical study to illustrate that membership model divergence does occur in organizational teams – and test a series of hypotheses built around two research questions: What are the causes of membership model divergence, and what are its effects on emergent team processes and states? Third, I propose a model of membership model divergence that links its antecedents, mechanisms, and effects.
In so doing, I challenge a fundamental assumption found in many of our existing theories of teams – that teams are by definition well-bounded. Though rarely stated explicitly, this assumption plays a critical role in both how we define teams and how we build theories to understand and predict behavior within them. When assumed, membership model agreement becomes a boundary condition that dually prevents us from using our theories to understand teams exhibiting membership disagreement and conversely from using insights gained from studying such teams to refine our theories. Both consequences are increasingly relevant given organizations’ widespread use of teams that are geographically dispersed, dynamically-composed, and overlapping. By exploring the drivers and effects of membership model divergence, we begin to reconsider our view of boundedness and to identify within precisely which contexts our existing theories can be used, in which they require modification, and in which they are inapplicable. Through exploring membership model divergence I also address a gap in our understanding outlined by Guzzo and Dickson in their call for research “to clarify issues of inclusion and exclusion by virtue of team boundaries, how boundaries relate to effectiveness, and how the nature of boundaries might shape the effects of interventions intended to raise team performance” (1996: 332). I also identify the practical costs of membership model disagreement and its effects on team performance, thereby contributing to our understanding of the relationship between teams’ structures, their emergent dynamics, and outcomes. These consequences of membership model divergence – both theoretical and practical – are playing an ever expanding role given organizations’ increasing use of teams that are dynamically-composed and overlapping.

MEMBERSHIP MODEL DIVERGENCE: DEFINITION, PREVALENCE, AND MECHANISMS

As membership model divergence is a new construct that has not yet been theorized about or empirically assessed, I outline its conceptualization according to four questions: 1) What is “membership” and “membership model divergence”? 2) Why does it matter if a team’s membership models diverge? 3) What mechanisms lead to membership model divergence? 4) Why and where is membership model divergence increasing?
What is “membership”?

Before discussing divergence in membership models, it is important to clarify what is meant by “membership”. Lickel and colleagues observed that: “much of what people consider important, from the work they accomplish to the emotions they feel, is influenced by their membership in groups” (2000; p. 223). Three approaches to determining membership can be discerned in theories and research on teams and groups, which I characterize as formal (based on an official team roster), identified (based on self- and others’ identification), and emergent (based on patterns of interaction). These draw respectively on three different underlying bodies of scholarship, reflecting organizational design, social psychological, and social network perspectives on teams, and are summarized in Table 1 and Figure 1.

Complicating our consideration of membership, the different members of a team can base their membership model on any, some, or all of these conceptualizations and use different criteria to evaluate each one. An interesting illustration is provided by contract workers, who are increasingly used in a wide range of industries (Barley and Kunda 2004). Formal rosters may or may not include contract workers as a matter of organizational policy. Team members and contract workers themselves may regard them as part of the team or as part of an external group (such as consultants or independent experts) (George and Chattopadhyay 2005). Their level of day-to-day interaction with individual teammates and the team as a whole may vary significantly due to factors like bounds on the transmission of intellectual property. Whether or not a contract worker is included in a given team member’s membership model is therefore contingent on multiple considerations within each conceptualization of membership (formal, identified, or emergent), as well as the relative weighting of the three conceptualizations themselves.

Making matters even more complex, each team member’s definition of membership may vary over time and across situations (Smith et al. 2012). For example, an individual may define his or her...
team on the basis of the official roster at the time of launch, but rely more on emergent relationships as the team works together over time. Similarly, one might rely on a team’s formal membership when considering employee appraisals, but informal membership when seeking advice. Despite this complexity, with the exception of studies of informal networks, researchers have typically taken membership as a given, rarely questioning its basis. Indeed, team members themselves typically accept membership at face value even if it has different bases.

For the purposes of this study I consider all three approaches to membership attribution and I examine the effects of the misalignment of membership models irrespective of the conceptual bases of those models. Importantly, members of the same team can hold misaligned models of team membership, whether due to differing models created from the same approach (e.g., two team members with different emergent models of the team) or to differing models based on differing approaches (e.g., one team member attributing membership on the basis of a formal roster, another on the basis of self-identification).

What is membership model divergence?

I define membership model divergence as the misalignment of team members’ models of who are and who are not team members. A mental model has been defined as a “psychological representation of the environment and its expected behavior” (Holyoak 1984 p. 193), typically arising through social interaction (Fiske and Taylor 1991), and used by individuals to interpret events, predict future behavior and states, and guide their actions (Rouse and Morris 1986; Walsh 1995). Membership model divergence occurs when a team’s members hold mental models of its membership that do not fully align.

Although mental models are individually held, their most powerful and widely studied effects are felt at the level of the group, as a consequence of their being – or not being – shared (for a meta-analysis and review see: DeChurch and Mesmer-Magnus 2010b; Mohammed et al. 2010 respectively). An important theoretical and methodological consideration, therefore, is the level of analysis at which to explore such misalignment. Given that divergence in mental models occurs at the
level of the team, and that the primary antecedents and consequences of mental models similarly exist at the collective level, I conceptualize membership model divergence at the level of the team.

**Why does it matter if a team’s membership models diverge?**

For teams, divergence in membership models is likely to increase coordination costs, and potentially confusion or even conflict, ultimately decreasing performance. For scholars, the existence of membership model divergence calls into question a fundamental assumption of many theories of teams and team dynamics – that teams agree upon their membership – thereby threatening their applicability and validity.

**Practical implications: Increased coordination costs, confusion, and conflict**

Research has consistently found that when mental models are shared across the members of a team, it is easier for those individuals to coordinate their actions and ultimately enhance their performance (Cannon-Bowers and Salas 1990; Cannon-Bowers et al. 1993; DeChurch and Mesmer-Magnus 2010a, b).\(^1\) Importantly, shared mental models facilitate team-level cognitive structures and processes such as transactive memory, whereby members use their understanding of the team’s knowledge to more effectively and efficiently manage the storage and retrieval of information (Brandon and Hollingshead 2004; Hollingshead 1998; Moreland et al. 1996; Wegner 1987), with well-documented performance benefits (Austin 2003; Ellis 2006; Lewis 2004; Moreland and Myaskovsky 2000).

When teams lack shared mental models, they may interpret information and events differently, leading to confusion, misunderstanding and conflict (Rouse et al. 1992). Moreover, the time and effort required to explicitly communicate and coordinate their divergent models adds a substantial coordination cost (Mathieu et al. 2000). This led Mohammed et al to argue that “both team

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\(^1\) This research has focused on cases where teams must work interdependently to accomplish their goal, particularly where there is an expectation that all members have a shared perspective. This provides an important boundary condition, as diverging models are less likely to be problematic in teams which are extremely large or poorly-defined, since it is anticipated that members will have a different understanding of the team (e.g., across a 100- person automotive development team).
successes and failures speak to the necessity of members being ‘on the same page’ with respect to what tasks to perform and with whom to coordinate actions,” (2010 p. 877), noting that “empirical studies have consistently shown [team mental models] to be of substantial benefit to both team processes and performance” (2010: p. 878). We would therefore expect membership model divergence to be associated with the same high coordination costs as any other unshared mental model.

Beyond the effects of unshared mental models described above, membership model divergence affects teams’ formation of other types of mental models – by determining from whom members gather the information used to form mental models of other aspects of the team. Individuals look to those around them to learn about their team (Bettenhausen and Murnighan 1985) and, as noted by Hackman, team boundaries frequently delineate the “social universe” (1992 p. 201) which serves as a reference, and from which members gather relevant data on the team’s task, roles or norms. Importantly, membership model divergence means different members will look to different sets of people when gathering information. As every individual has different knowledge, experience and behavior, the mental models that a team’s members derive from interactions with different sets of people will themselves vary.

Therefore, in addition to being a direct (first-order) source of confusion and conflict, membership model divergence also increases the likelihood that other mental models will be unshared (second order effect) – reinforcing and magnifying the coordination issues noted above. For example, it may come into play when members try to divide the workload fairly, due to differing models of who and how many people are members (first-order effects), or over misaligned expectations of behavioral norms (second-order effects) resulting from members learning team norms by looking to different sets of colleagues (reflecting their different membership models) as a reference.

**Theoretical implications: Challenging a fundamental assumption of teams theory**

Membership model divergence calls into question a core assumption underlying much of the existing theory on teams – i.e., that team membership is well defined, and consequently that teams are well bounded. Scholars have defined a teams as *a stably bounded set of individuals working*
interdependently towards a common goal (Alderfer 1977; Cohen and Bailey 1997; Guzzo and Dickson 1996; Hackman 1987; Sundstrom et al. 1990). Core to this definition is the idea that teams are “well-bounded” with boundaries that are both clear and appropriately\(^2\) permeable (Alderfer 1980; Hackman 1987, 2002). These early treatments established the role of boundaries as barriers as well as differentiators. The role of boundaries as barriers underlies theories of boundary spanning (Ancona and Caldwell 1992a; Marrone et al. 2007), while their role as differentiators underlies social psychological theories, which argue that membership in an entitative group (Brewer and Harasty 1996; Hamilton et al. 1998; Lickel et al. 2000) will affect actors’ perception, cognition and behavior (Hogg and Terry 2000)

Membership model divergence directly challenges the assumption of a well-bounded team by showing how perceptions of a team’s boundaries may vary across members. The assumption of a well-definable boundary has recently been challenged by multiple scholars. Mathieu and colleagues (Hitt et al. 2007; Mathieu and Chen 2011) argued that teams are inextricably embedded in a multi-level work system, necessitating a similarly multi-level approach to their analysis. This systems-level view has also been advocated in work by Marks, DeChurch and colleagues (DeChurch and Marks 2006; Marks et al. 2005; Zaccaro et al. 2011) on multiple-team systems. Similarly, recent work on multiple team membership has argued that teams frequently share members (Mortensen et al. 2007; O'Leary et al. 2011a; O'Leary et al. 2011b). Common to all is the notion that team boundaries are increasingly harder to pinpoint, leading Mortensen (2012) to suggest that we reconsider our view of boundedness as a defining element of teams. Building on these arguments, membership model divergence reduces boundedness, calling into question the applicability and validity of theories based on the premise of well-bounded teams.

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\(^2\) In Alderfer’s early formulation, he emphasizes the importance of neither over, nor under-bounding teams. However most subsequent work has focused primarily on the effects of the latter.
What are the mechanisms leading to membership model divergence?

As team members form mental models to represent their understanding of the environment as experienced through interaction with teammates (Marks et al. 2001), divergence in a team’s membership models can arise either from differing underlying information or from their differing interpretations of that information. I focus on exploring the first. Information will be shaped by the team’s design (e.g., geographic distribution, team size, concurrent membership on multiple teams) as well as by its emergent dynamics (e.g., time spent working in the team; the quantity and pattern of team interactions). For example, within a geographically dispersed team one might expect members’ experiences to vary from one site to another, yielding different models of who is (and is not) in the team. Similarly, if members work on the team part time, their models are likely to be less consistent than if all members were fully dedicated to it. Such variations are more clearly visible and measurable as team-level factors than variations in individual-level cognition or intentionality. In addition, design and structural factors are more easily observed and manipulated, making them more directly accessible and useful for those seeking to shape team membership model divergence.

Though not the focus of this study, it is worth noting that cognitive bias (e.g., over-weighting the importance of more recently acquired information), beliefs and preferences (e.g., a tendency to favor inclusiveness over exclusiveness), or intentionality (e.g., excluding someone as a means of limiting access to resources or withholding prestige) may all contribute to members interpreting information differently.

Why and where is membership model divergence increasing?

If scholars have found relatively little evidence of membership model divergence, it can be attributed in part to their not looking for it and in part from changes in the nature of team-based work that are increasing the frequency and degree of divergence. While many characteristics of a team may be hard to discern, open to interpretation, or dynamic (e.g., interpersonal dynamics), membership tends to be viewed by scholars and practitioners alike as unambiguous and commonly held (Diehl 1990). Hence they are less likely to question or seek clarification about team membership than they are for the factors underlying a team’s mental models on other dimensions. This is compounded by a
tendency to refer to teams by names (e.g., “the Alpha team”) rather than by their membership, thereby masking differences in models. This “assumption of agreement” is embedded in social psychology theories built around a sense of entitativity (Brewer and Harasty 1996), which fosters the view of membership as a given.

Moreover, divergence in membership models has often been empirically obscured or eliminated through study design. For example, in some cases, field researchers have provided teams with membership lists and told subjects to respond with respect to those lists (e.g., Ancona and Caldwell 1992a; Ancona and Caldwell 1992b) while in others, experimental studies have been built around artificially created laboratory groups with fixed and clear membership. In evidence of this, in both theory and research on shared mental models, one of the few factors not examined is the team members’ model of the team itself.

In addition, recent shifts in how teams are used may be increasing the incidence of membership model divergence. For the most part, theories have been built around a characterization of teams as having stable, non-overlapping, and collocated membership, whose time is spent collaborating with a clearly-defined set of teammates, thereby establishing a common mental model of membership. In recent years, the increased use of globally distributed teams (Schiller and Mandviwalla 2007), teams in which members fluidly enter and exit during its lifetime (Thiry and Deguire 2007), and teams with concurrently overlapping membership (O’Leary et al. 2011a) does not match the traditional model of the team (Mortensen 2012). To the extent that these phenomena represent a shift in the way in which teams are used in practice, they increase the likelihood of membership model divergence by increasing the variation in the information teams use to create their membership models.

In a globalized world, teams are frequently dispersed across substantial distances. Distributed\(^3\) teams require members to collaborate with colleagues in different physical locations, time zones, and activities.

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\(^3\) Within the extant literature, the terms “global”, “virtual”, “dispersed”, “distributed”, and “far-flung” have all been used to describe the same basic phenomenon.
cultures, languages and configurations (for discussions of these dimensions see: Gibson and Gibbs 2006; O’Leary and Cummings 2007). Their members’ experiences are widely divergent since collaborators are embedded in different contexts. Given the rapid pace of change, growing product complexity, and the demand for customer-focused innovation, organizations increasingly rely on project-based teams that are assembled to work on specific short-term projects and disbanded upon completion (Brown and Duguid 2001; Hobday 2000; Prencipe and Tell 2001). Such teams have been described as “short-term and fluid” (Prencipe and Tell 2001) and as “self-contained, complex and temporary” (Grabher 2002), involving specialized employees organized around “short-term project objectives” (Lindkvist 2004). As not all team members start and end their work on a given team at the same time – entering and leaving as their particular expertise is needed – this means different team members have very different experiences based on the timing of their entry and exit.

Moreover, as project teams are designed to leverage employees’ differentiated skills (Lindkvist 2004), those with unique skills increasingly find their time divided across multiple teams (e.g., Hobday 2000). The overlap between any two teams can range from ‘none’ to ‘complete’, and shift over time as different projects operate on different temporal rhythms, such that an individual may be an active member of a given project at certain times and have little interaction with it at others (for a discussion see O’Leary et al. 2011a). Such multi-teaming frequently occurs within the context of a single multi-team system (Mathieu et al. 2001) with an overarching goal, which may make it more difficult for members to differentiate across multiple teams within the same system.

Compared with the traditional characterization of a team (collocated, non-overlapping and stable) individuals spend less time in each team, enter/exit the team at different points, and dedicate only a portion of their time to that team. Consequently, time spent working together, creating a shared experience and a shared definition of the team is reduced. Scholars of distributed work have observed this phenomenon within dispersed teams, identifying a “mutual knowledge problem” (the lack of shared information) as a major impediment to distributed team functioning (Cramton 2001). Similarly, scholars of project-based work have found that fast-moving project-based teams have difficulty establishing a shared understanding and common knowledge base (Lindkvist 2004). This
makes membership model divergence particularly likely to occur in contexts that rely heavily on dispersed, dynamic and overlapping teams.

However, while the notion that such types of teams are on the increase has face validity, we lack empirical evidence to prove it. Nevertheless, to the extent that these characteristics are present, membership model divergence is likely to arise, and is likely to increase to the extent that these characteristics increase in the future.

Summary

In summary, I argue that: 1) membership is a critical driver of team dynamics; 2) divergence in membership models is likely to have effects above and beyond that of unshared mental models, based on other aspects of the team; 3) a key driver of divergence in membership models is differing information held by team members; and 4) changes in the nature of work are increasing the likelihood that the information used by a team’s members to form their models of membership will diverge.

In the following sections, I present hypotheses and analyses to test a model of the antecedents and effects of membership model divergence. As it is beyond the scope of this study to test all mechanisms and drivers, I focus on a set of factors directly related to the trend towards dispersed, overlapping and fluid membership. Rather than being an exhaustive testing of antecedents, I seek to determine if these factors are indeed drivers of membership model divergence. Other shapers of membership model divergence are worthy of future investigation and should be pursued (regardless of which is the strongest), since it is seemingly obvious to both scholars and practitioners “who is in the team” – that is, they assume agreement on this point.

HYPOTHESES

Given the important and distinct roles of a team’s initial design (Hackman 1987), the processes that emerge dynamically (Ilgen et al. 2005; Marks et al. 2001) and the likely causal links between them, I categorize the antecedents in my model into two groups. Proximate drivers capture emergent states and processes which directly increase or decrease information variation, while underlying conditions capture the initial characteristics of the team that give rise to the proximate drivers, thereby indirectly affecting membership model divergence. I similarly divide the effects of
membership model divergence into *proximate* and *distal outcomes*, with the former being emergent states and processes that are affected by membership model divergence, and the latter the consequences thereof. The relationships between the specific drivers and effects of membership model divergence hypothesized in this study are presented in Figure 2 and discussed as Hypotheses 1 through 3.

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Insert Figure 2 about here
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**Proximate drivers of membership model divergence**

The proximate drivers relating to membership model divergence operate through the two mechanisms outlined above—the information used by members to create their membership models and their interpretation of that information. I focus on two factors that may affect how much a team’s membership models diverge: the amount of time spent by members with the team, and differences in members’ experiences of working together.

**Exposure will be negatively related to membership model divergence**

The more a team’s members are exposed to one another (either through time dedicated to the team or quantity of explicit task-based interaction), the more shared their mental models are likely to be (Smith-Jentsch et al. 2005). With respect to membership model divergence, the more the members of a team are exposed to one another, the more shared information they are likely to hold about who are and who are not members of the team, and the less divergent their membership models are likely to be.

Team members’ shared experiences are used as the basis of the team’s membership models (Klimoski and Mohammed 1994; Rentsch and Klimoski 2001). For example, working through the night to successfully meet a critical deadline is likely to solidify the team’s membership in its members’ minds. Exposure to the team provides explicit information about who is and is not considered a member. For example, a discussion about how to divide a team bonus requires explicitly identifying the members of the team. The greater the exposure, the less the membership model
divergence since exposure increases the commonly-held information used as the basis of forming membership models.

Exposure can take two distinct forms: time dedicated to the team and explicit interactions. It is widely acknowledged that employees must divide their focus and time across an ever-increasing number of tasks and work structures (Perlow 1999). Indeed some scholars take the view that the organization exists to channel members’ attention towards some activities and away from others (Ocasio 1997). Time allocation is a critical structural determinant of the attention a team’s members can and do pay to it (Cummings and Haas 2011), thereby shaping the information they can access when constructing their membership models. Explicit interaction among team members (one-to-one, one-to-many, or many-to-many communications that take place either face to face or via mediating technologies) also play an important role. Teams vary significantly in the volume of explicit interaction that occurs among their members, which in turn shapes their understanding of the team and its processes as well as the environment as a whole (Berger and Luckmann 1966). Recent work by Metiu and Rothbard (2012) has highlighted the critical role of interaction among team members in creating a mutual focus and understanding of the task. This underlies Lickel and colleagues’ finding that amount of interaction is central to the way individuals characterize their team (2000), and to its sense of group entitativity (2001). While copresence and explicit interaction are clearly related, it is possible for them to diverge as in the case of a team in which members are fully dedicated (with respect to time) but are able to work independently for much of the time.

Turning first to time dedicated to the team, as noted by O’Leary and colleagues (2011a), the less time team members dedicate to a given team, the less time they have to share experiences from which they gather the data that forms the basis of membership models. Compounding this, the less time all members dedicate to the team itself, the less likely they are to share in any one experience, as the time one member dedicates to the team may not overlap with that of another (O’Leary et al. 2011a). Moreover, when a team’s members dedicate less of their time to the team, they have less opportunity to observe specific evidence of who is and who is not a team member.
Similarly, interactions are themselves shared experiences that produce a shared reality (Collins 1990, 2004). Therefore the more a team interacts, the more its membership models will be based on shared experience, which is used for membership decisions as well as to shape team members’ interpretation of that information. These arguments underlie Rentsch and Klimoski’s claim that the more a team’s members interact, the more likely it is that they will develop shared understandings (2001), and are reflected in Metiu and Rothbard’s (2012) finding that interaction within a group increases mutual focus on the group’s task. At the same time, the more a team interacts, the more opportunities its members have to share information that is specifically about team membership. Given the bias towards sharing information that is already commonly held (Stasser and Titus 1985), the information shared in such interactions is likely to be reinforced over time, establishing a common body of knowledge about the membership of the team.

Together, this evidence suggests that the greater the exposure of the team’s members to each other as a result of the time dedicated to the team and explicit interactions, the more likely they are to share experiences and explicit membership information, and the less likely it is that their membership models will diverge.

Hypothesis 1a: The larger the portion of their time that a team’s members dedicate to the team, the less its membership models will diverge.

Hypothesis 1b: The more a team interacts, the less membership model divergence it will exhibit.

Variance in the pattern of interaction within a team will be positively related to membership model divergence.

Providing an important caveat to the argument presented above, research on social networks has found that the pattern of interaction within a group is rarely uniform, but tends to vary from one member to another with respect to with whom and how frequently each member interacts) from one member to another. For example, the interaction networks of the members of a team may vary in terms of density of ties, centrality of particular actors, and the existence of cliques or other substructures (for discussions of network structures see Wasserman and Faust 1994). This acts as a
countervailing force to that outlined in the earlier section. To the extent that the members of a team differ in their interaction patterns, so will the information they gain through those interactions and the experiences they use to interpret that information, hence the more divergent their membership models are likely to be.

Early work on intra-group communication (Bavelas 1950) found patterns of interaction differed dramatically within teams, ultimately affecting team outcomes. This has been reinforced by research on social networks (e.g., Sparrowe et al. 2001), and more recently on virtual and distributed teams (e.g. Potter and Balthazard 2002; Wiesenfeld et al. 1999). Given that mental schema are built incrementally through repeated interactions (Fiske and Linville 1980), to the extent that they differ, the resulting mental models will differ as well. The idea that the more variance there is in the patterns of interaction within a team, the more variance there will be in their experiences echoes recent work on collective intelligence, which found that teams in which some members dominated discussions were less collectively intelligent (Woolley et al. 2010).

As posited in H1a and H1b, interactions are an opportunity to collect information specifically on who is and who is not a team member, hence the greater the variance in interactions, the more likely it is that divergent membership models will emerge.

Hypothesis 1c: The more variance there is in the patterns of interaction within a team, the more membership models will diverge.

Underlying conditions leading to membership model divergence

The proximate drivers of membership model divergence outlined above are dynamic properties that emerge as a result of the team’s ongoing interaction. Underlying such properties is a series of more persistent, structurally-based characteristics that stem primarily from the design of the team, such as overlap with other teams (in the form of multiple team membership), geographic distribution of members, and team size.

Multiple Team Membership will be negatively related to the time dedicated to the focal team

Research by Zika-Viktorsson et al. (2006) found that organizations increasingly assigned employees to work concurrently on multiple teams. At the same time, scholars have begun to explore
the relationships between multiple team membership and factors such as a team’s attention (Leroy and Sproull 2004), distribution (Cummings and Haas 2011), effectiveness (Mortensen et al. 2007), technology (Bertolotti et al. 2012), and learning and productivity (O’Leary et al. 2011a). As noted by Cummings and Haas (2011), time allocation across multiple teams is a structural feature of team design that fundamentally shapes the focus of members’ attention to the team. In short, the more members are shared with other teams, the less time they have to dedicate to the focal team. As outlined earlier, this limits opportunities for interaction within the team, thereby reducing the shared experience essential to align members’ membership models.

Hypothesis 2a: The more a team’s membership overlaps with other teams, the less time its members will spend on the focal team, thereby increasing membership model divergence within the team.

Geographic distribution will be negatively related to time dedicated to the focal team

As a result of globalization and technological advances, geographically distributed teams are becoming more prevalent, allowing organizations to leverage dispersed resources, reduce costs and be more responsive to market changes (Cummings 2004; Gibson and Cohen 2003; Gray and Meister 2004; Malhotra et al. 2001; Townsend et al. 1998). This affects not only a team’s composition, interpersonal dynamics and work structure, but also the time that members devote to it. Cummings and Haas (2011), for example, found that geographically distributed teams were more likely to have “high-demand” members, who in turn dedicated less time to the team task. Research on visibility in distributed teams found that it was difficult to keep dispersed team members and tasks in mind (Hinds and Bailey 2003), increasing the likelihood that members were “over-assigned” in terms of numbers of tasks. Other research revealed a lower volume of spontaneous interaction in distributed teams (Hinds and Mortensen 2005), reducing the opportunity for unplanned task-related work. Furthermore, distribution increases the competing demands on a team’s members through the proximity of local colleagues seeking to pull their attention away from the focal team (Armstrong and Cole 2002). Similar arguments underlie Barkema et al.’s (2002) claim that knowledge-intensive teams are less
likely to work together full time on a single team in the same location. Thus, I posit that geographic distribution will reduce the time a team’s members dedicate to it.

Hypothesis 2b: The more geographically dispersed a team is, the less time its members will spend on it (thereby increasing the amount of mental model divergence the team will exhibit).

Geographic distribution will be positively related to variance in a team’s interaction patterns

Research on geographically distributed teams has found that the structure of the team itself affects the emergent dynamics within it. Structural subgroups, imbalance, and the presence of geographic isolates shape both affective and cognitive characteristics of teams (O’Leary and Mortensen 2010). A team’s structure, however, does not impact all members in the same way since geographically distributed teams are rarely fully distributed (i.e., every member is a geographic isolate). More commonly, distributed teams consist of some combination of collocated subgroups and isolates. Given that spontaneous interaction is rarer in distributed than collocated teams (Hinds and Mortensen 2005), members have more opportunity to interact with collocated teammates than those at other sites. These frequent face-to-face interactions with local colleagues are also richer than mediated interactions with distant teammates (Daft and Lengel 1986). This was borne out by Panteli and Davison’s (2005) study of geographically distributed teams, which found that geographic subgroups were one of the most powerful direct shapers of interaction patterns, with team members communicating significantly more with their collocated teammates. Thus distributed teams are likely to exhibit greater variance in members’ interaction patterns than teams that are collocated.

Hypothesis 2c: The more geographically dispersed a team is, the more variance there will be in the interaction patterns of its members (thereby increasing membership model divergence within the team).

Team size will be positively related to variance in a team’s interaction patterns

Team size affects the variance in a team’s interaction patterns through two mechanisms. First, combinatorially, larger teams have more other members with whom a given team member may interact (for example: while there are six potential dyadic interactions that can occur in a four person
team, there are 14 possible interactions in a team with six members). Knowing nothing about the
drivers shaping team members’ interaction choices, this means that more variance in interaction
patterns is possible within larger teams. This is related to the argument that larger teams have greater
potential for dissimilarity because they include more members who themselves may be distinct (e.g.
Smith et al. 1994; Wiersema and Bantel 1992). Second, beyond increasing the possible complexity of
interaction patterns within a team, team size also increases the number of members whose interaction
patterns may differ. These mechanisms underpin the argument that team size is negatively related to
the development of a shared team mental model (Cannon-Bowers et al. 1993; Klimoski and
Mohammed 1994; Rentsch and Hall 1994). As noted by Rentsch and Klimoski (2001), the argument
uses size as a proxy for opportunities for team member interaction.

Hypothesis 2d: The larger the team, the more variance there will be in the
interaction patterns of its members (thereby increasing the
membership model divergence within the team).

Team size will be negatively related to the amount of interaction within a team

In larger teams, interaction is diffused across more potential targets, thereby reducing the
number of interactions each team member engages in. For example, team size has been found to be
negatively related to quantity of informal communication within top management teams (Smith et al.
1994). More broadly, the members of larger teams participate less than those of smaller teams (Curral
et al. 2001; Guzzo and Salas 1995). Moreover, as team size increases, the evenness of communication
within that team declines as a smaller and smaller proportion of members dominate the discussion
(Shaw et al. 1981). Relatedly, team size has been linked to lower involvement on the part of team
members (McGrath 1984), as well as to greater likelihood of social loafing (Karau and Williams
1993; Latane et al. 1979). Hence within larger teams, individual members are likely to be less actively
involved with the task and the team itself, thereby reducing their likelihood of interaction. Mueller
recently built on this paradigm to argue that larger teams result in lower individual performance due
to relational loss – frequently tied with the amount of interaction (Mueller 2011). Thus, as teams grow
in size, communication between any given members will be reduced.
Hypothesis 2e: The larger a team is, the less interaction there will be among its members (thereby increasing the mental model divergence the team will exhibit).

**Proximate and Distal Outcomes**

Parallel to the proximate drivers and underlying conditions, I identify both proximate and distal outcomes of membership model divergence. Membership model divergence will be negatively related to performance through effectiveness of transactive memory.

Research on mental models has found that the convergence of team mental models is positively related to the effectiveness of coordination (Marks et al. 2002). Mathieu and colleagues found shared team mental models were indirectly linked to performance, operating through team processes (Mathieu et al. 2000). In line with this, I posit that membership model divergence will have a negative effect on a team’s performance by reducing the effectiveness of its transactive memory system.

Effective transactive memory systems coordinate content knowledge as well as meta-knowledge about the location of expertise within a group (Wegner et al. 1991). They allow team members to categorize, store and retrieve information in a way that maximizes a team’s breadth and depth of knowledge while minimizing redundancy and recall effort (Hollingshead 2001). Effective transactive memory systems are characterized by: knowledge specialization (i.e., the differentiation of knowledge across members), knowledge coordination (i.e., awareness of who has what knowledge and how to access it) , and knowledge credibility (i.e., trust in the knowledge held by other members) (Liang et al. 1995).

Transactive memory is an established predictor of team performance (Lewis 2004). Effective transactive memory systems boost performance by reducing the time and effort wasted on coordination miscues, searches for external knowledge and assistance, and misuse of available knowledge (Austin 2003). Knowledge of member skill-sets and expertise also enables teams to approach problems more flexibly (Moreland et al. 1996), thereby allowing for more novel solutions.
An effective transactive memory system allows a team to efficiently manage the knowledge held by its members.

Conversely, in cases where members base their actions on different models of team membership, there is an increased likelihood of unintentional redundancies or gaps in information transfer. Moreover, when new information must be assimilated into the team’s body of knowledge, differing membership models may result in confusion over who is responsible for attending to and integrating knowledge within a particular domain, allowing some information to fall through the cracks. When the team needs to retrieve knowledge, membership model divergence may lead to confusion over whose expertise is most relevant. Breakdowns in information storage or retrieval that arise from divergent membership models may be seen as failures by certain members to fulfill their responsibilities and undermine their credibility as perceived by their teammates – another key driver of transactive memory effectiveness. The link between transactive memory effectiveness and performance implies an indirect effect of membership model divergence on performance operating through transactive memory, in line with prior research which found that disagreement over team boundaries had a negative effect on expertise identification and allocation (Mortensen and Hinds 2002).

Hypothesis 3a: The more membership model divergence a team exhibits, the poorer it will perform.

Hypothesis 3b: The relationship between a team’s membership model divergence and performance will be mediated by the effectiveness of its transactive memory system.

METHODS

To understand the antecedents and effects of membership model divergence, I conducted a survey-based study of software development teams in a single division of a large, multinational software company. The teams studied were formal, well established (i.e., not ad-hoc), and project-based. The organization explicitly named all teams in the sample (e.g., the “Financial Module team”) and in all cases official management-sanctioned team rosters existed. To gain a richer understanding
of the teams, their work practices, the challenges they faced, and their performance, the surveys were followed by semi-structured interviews with a randomly-selected subset of those surveyed. To test the relationships proposed in my model, I used structural equation modeling (SEM) with maximum likelihood estimation to analyze the saturated measurement model, the structural model corresponding to the full set of hypotheses, and the individual hypotheses.

Data collection procedure and sample

Official team rosters were used to identify each team, thereby ensuring a consistent starting point. Given that this study was designed in part to illustrate that rosters do not fully capture a team’s perception of its membership, this decision clearly has implications for the focal phenomena. I opted to start from official rosters to align this study and increase comparability with prior research which relied on official team rosters (e.g., Ancona and Caldwell 1992b). Importantly, while my sample itself was bounded based on the official team roster, respondents were allowed to answer about individuals not on the official roster. In this way, the design of the study sought to address some of the shortcomings of prior research that did not allow respondents to verify team membership.

The survey was divided into two phases, administered approximately two weeks apart and sent to the same individuals – those named on the official management-sanctioned team roster. Phase 1 was used to collect data on team member demographics and membership models, and Phase 2 to gather data on respondents’ perceptions of the team and their teammates (all antecedents, effects, and controls in the tested model). Both surveys were tailored to each recipient such that all questions explicitly named the team as defined by the team manager. For example, all members of the Alpha team received surveys with cues of the type “How long have you been a member of the Alpha team?” The sample surveyed in Phase 2 was identical to that of Phase 1.

I initially contacted 443 individuals in 49 teams. Excluding teams where less than 60 percent of members responded or with fewer than 3 respondents reduced the sample to 38 teams (378 respondents). I chose the 60% threshold based on an examination of the data which exhibited a discontinuity, with a rapid drop in completion rates below 60%. The mean non-response rate for teams in the final sample was 19 percent (1.74 per team), with interviews suggesting non-respondents
were not systematically different from the rest of the population, as the interview responses of survey non-respondents were not themselves qualitatively different from those of survey respondents. The majority of team members (65 percent) worked as developers or in related fields (user interface design, quality, etc.) creating, maintaining and supporting highly interdependent code; 27 percent worked as project or development managers; and the remaining 8 percent worked in marketing, as technical writers or in related fields. The mean number of teams of which each respondent was a member was 1.81. Of the 38 teams in the sample, 27 were geographically dispersed, with team members in as many as five locations. All respondents considered themselves members of the teams named by their managers.

**Measures**

**Membership Model Divergence**

I used two approaches to capture respondents’ assessments of team membership – one based on freeform recall and one based on list verification. In the Phase 1 survey, respondents were first asked to: “Please take a moment to list all the members of the XXX Team” and provided a freeform space in which to do so. Later in the Phase 1 survey, respondents were asked to verify the accuracy of a list of team members according to the team’s manager: “Please indicate which of the following individuals you consider to be a current member of the XXX Team.” This second question did not reference the previous question or respondents’ freeform answers. A similar verification question was also asked in the Phase 2 survey, which included a similar list and told respondents: “We realize that your perception of the team may differ somewhat from this list. Please take a moment to identify which individuals from the following list you would consider to be members of the XXX Team and which you would not.” In both verification questions, respondents were able to both add and remove names from the provided lists. However, as the lists generated in both Phase 1 and Phase 2 verification questions were almost identical, I opted to use the Phase 1 data to represent the verification approach as it was collected prior to the outcome measures.

The freeform approach used in Phase 1 reflected the model of membership that team members held in their minds absent any prompting, but risks errors in recall (i.e., forgetting to include
a teammate). In contrast, the verification approach used in both Phase 1 and Phase 2 avoided this recall error by providing a list for respondents to vet, but in so doing introduced a bias by providing them with a management-sanctioned membership list to start from. Based on these questions, I created three measures of team membership reflecting the freeform lists, verification lists, and the intersection of the two (those named as members in both). Although the verification lists were slightly more inclusive than the freeform lists, they yielded similar patterns of relationships to the constructs in the study. I therefore used the Phase 1 verification format data for the analyses in this study because its strong priming towards agreement with the management-sanctioned list provided a conservative data source, and because it reflected the model of team membership that team members were able to call up and use as needed.

In the absence of an existing empirical measure of membership model divergence, I drew on related prior theory to create one. As noted by Mohammed et al. (2010), research on shared mental models has frequently focused on two dimensions: model similarity and model accuracy. In line with this, I created two distinct measures. The first, inter-member membership model divergence, captured divergence among team members’ models and is analogous to model similarity in the shared mental models literature. The second, member-manager membership model divergence, captured divergence between member models and the model held by the team manager, and is analogous to model accuracy. I used both inter-member and member-manager membership model divergence as indicators of a latent variable of overall membership model divergence.

To calculate the measure of inter-member membership model divergence (MMD_{IM}), I made a pairwise comparison between each pair of respondents within a team as to whether they agreed or disagreed on the membership of each other person named on their manager’s list of team members. I coded the agreement of each pair of respondents within a team regarding each potential member named by either respondent: 0 if the respondents agreed on the target’s membership (either both included or both excluded) and 1 if they disagreed (one respondent included the target while the other
The total number of disagreements between each pair of respondents was then divided by the total number of unique individuals referenced by that pair, yielding a percentage of divergence.

\[
MMD_{\text{IM}(i,j)} = \frac{\sum_{\forall t \in \text{T}} [1 \text{ if } A_{it} \neq A_{jt}, 0 \text{ if } A_{it} = A_{jt}]}{\text{number of members in } T}.
\]

I used the mean of all pairs of respondents as the team-level measure of inter-member membership model divergence. To calculate the measure of member-manager membership model divergence (MMD_{\text{MM}}), I used the same procedure, comparing each respondent’s membership attributions against those of his or her manager. Figure 3 provides a graphical representation of a hypothetical team and the membership model divergence calculations based on it.

\[\text{Insert Figure 3 about here}\]

Taking Figure 3 as an example, in which the team manager’s model includes \([A,B,C]\), member A’s model includes \([A,B,C,D]\), and member B’s model includes \([A,B,C,F]\). A and B’s models diverge on two \([D,F]\) out of a total of five \([A,B,C,D,F]\) targets referenced, yielding a percentage of divergence of \(2/5 = .40\). Similarly, A and C diverge on 1 of 4, and B and C on 3 of 5, yielding scores of .25 and .60 respectively. The mean divergence scores of \([A:B, A:C, B:C]\) yield an inter-member membership divergence (IM-MMD) score of .42. Following a similar approach, A and the team manager diverge with respect to one \([D]\) out of a total of four \([A,B,C,D]\) targets referenced \((1/4)\); similarly, B’s model diverges from the manager’s on 1 of 4 targets, and C’s diverges on 2 of 4, yielding scores of .25, .25, and .50 respectively, and a member-manager membership divergence (MM-MMD) score of .33.

Proximate drivers

**Average time dedicated to focal team.** To assess the portion of time a team’s members dedicated to the team’s task, I asked respondents to report the percentage of time dedicated to the team in question. The team-level mean was used as a measure of team time commitment to the focal team.

**Interaction mean and variance.** I created measures of interpersonal interaction using respondents’ self-report data on how frequently they interacted with each member of their team, either face-to-face or mediated by email, phone, voicemail, videoconference, teleconference, instant messenger, fax, or paper documents. I calculated mean levels of interaction within each team and used these as measures of average intra-team interaction. I calculated the Euclidean distance between each pair of team members based on their pattern of interaction with all other team members. I then used the mean of those Euclidean distance scores as a measure of intra-team interaction heterogeneity.\(^5\)

Underlying conditions

**Multiple Team Membership.** To capture the extent to which a team’s members were simultaneously members of other teams in the organization, I asked respondents to report the number of other teams of which they were currently members. I used the team-level mean of their responses as a measure of the extent of multiple team membership in the focal team.

**Geographic distribution.** To capture teams’ geographic distribution, I asked respondents to report their primary work location. I used this self-report data to generate measures of the five dimensions of distribution (spatial, temporal, site, isolation, and imbalance) outlined in O’Leary and Cummings (2007) as well as a dichotomous measure of distribution. I tested alternative structural equation models based on each of these measures of distance and found that the dichotomous measure of geographic distribution resulted in a model that was the best fit for the data. I therefore used the dichotomous measure of distribution in the reported analyses.

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\(^5\) I conducted Kolmogorov-Smirnov tests to assess normality and found that average interaction was non-normal \((z = 2.03, p<.01)\). The natural log yielded a more normal distribution which passed the test of normality \((z = .70, p>.20)\) but did not affect the pattern of relationships. The transformed variable was used in all subsequent analyses.
**Team size.** To capture team size, I compared two measures: the number of unique individuals named by the team manager, and the number of unique individuals named by survey respondents. Although the lists differed with respect to who they included, the two measures of team size were highly correlated ($r = .65 \ p < .01$); including either in the structural equation model yielded a similar pattern of results. This suggests that there was not a systematic bias towards inclusion or exclusion. Thus I used the count of individuals named by team members as it most closely matched the number of potential members being considered when respondents completed the survey.

**Proximate and Distal Outcomes**

**Transactive memory effectiveness.** I measured transactive memory effectiveness using Lewis’s (2003) measure, asking respondents to rate the accuracy of 15 statements about their team (e.g., “I have knowledge about an aspect of the project that no other team member has”) using a five-point Likert scale (1 = “not at all accurate”, 5 = “very accurate”). The mean of these ratings was then calculated to create a reliable ($\alpha = .87$) measure of transactive memory. The mean of all individual-level measures yielded a reliable ($\alpha = .96$) team-level measure of transactive memory. To verify that aggregation to the team level was justified, I estimated within-group inter-rater reliability scores based on the formula derived by James, Demaree, and Wolf (1984). The inter-rater reliability scores indicated that the team-level measure of transactive memory was justified ($ICC_1 = .21$, $ICC_2 = .80$, $r_{wg} = .96$).

**Performance.** To measure performance, I used member ratings of performance on seven dimensions (efficiency, quality, adherence to schedule/budget, work excellence, meeting customer/client needs, contributing something of value to the company, and technical innovation) relative to all other teams with which they had experience (Ancona and Caldwell 1992a). The mean of respondents’ ratings yielded a reliable estimate ($\alpha = .79$) of performance. However, a factor analysis suggested that the measure of technical innovation did not load with the other factors; removing it produced a measure of performance that was more reliable ($\alpha = .83$). I ran the reported models using both versions of the performance measure and found a similar pattern of results and significance. I therefore used the measure without technical innovation in the reported analyses. To validate the
accuracy of team member ratings, a sub-sample of team managers was asked the same question regarding the teams they managed. I found manager ratings had similar reliability ($\alpha = .85$), were significantly positively correlated to member ratings ($r = .63, p < .01$), and yielded similar patterns of correlation with other measures. However, given the small number of manager ratings, I used member ratings to assess performance.

Controls

I explored a number of control variables which prior theory suggested might impact perception or alignment of a team’s membership models. These included different structures of distribution (e.g., imbalance, isolation, time zone separation), type of interdependence (e.g., pooled, sequential, reciprocal), stage of task completion, and mean level and heterogeneity of demographic traits (e.g., age, ethnicity, education, tenure in team and company, and job category). These controls did not have significant effects on the key constructs in the model and I did not include them in the reported results in the interest of parsimony.

Identification. One control – identification with the team – was retained in the final model as it was significantly related to membership model divergence. Given the extensive literature on identification within teams and its sources and effects, there is reason to expect identification will co-vary with membership model divergence. On the one hand, to the extent that individuals hold differing models of who is in the team, they are likely to identify with different sets of people, thereby reducing the sharedness and, possibly, strength of their identification. At the same time, the more strongly the members of a team identify with that team, the more closely those members are likely to attend to that team and the more convergent the information used to form their membership models – leading to a reduction in membership model divergence.

It is also important to differentiate between the effects of convergence of membership models and identification, as theory suggests that identification may play a similar role to that of alignment of membership models. Therefore, in addition to the hypothesized constructs outlined above, I also included a control for level of identification. Given the existence of theory supporting a causal link from identification to membership model divergence and vice versa, I include it in the model as a
covariate of membership model divergence. I measured identification with the team using a 13-item scale adapted from Tyler (1999), in which team members rated statements (e.g., “I see myself as a member of the team”) on a five-point Likert scale (1 = “not at all characteristic,” 5 = “very characteristic”). The mean of the 13 items formed a reliable ($\alpha = .80$) score of how strongly the individual identified with the team, and inter-rater reliability scores indicated that combining them into a team-level measure of identification was justified given inter-class correlation coefficients (sample-wide, mean by team) of ($ICC_1 = .30$, $ICC_2 = .70$, $r_{wg} = .92$).

**RESULTS**

Membership model divergence existed in 28 of the 38 teams in the sample (72 percent), with a mean of .69 (s.d. = .52, values ranging from 0 to 1.68, see Table 2 for descriptive statistics and correlations).\(^6\) Within teams experiencing membership model divergence the mean was .93 (s.d. = .36), thereby providing evidence of the existence of naturally occurring membership model divergence.

Insert Table 2 and Figure 4 about here

I assessed model fit using several statistics. I used the Chi-square test that assesses the goodness of fit between the reproduced and observed correlation matrices. The non-significant Chi-square [$\chi^2(41) = 46.14, p = .27$] here indicated that the difference between the model in this study and the data is not significant (see Figure 4). Because the Chi-square test is highly sensitive to sample size, I also used three other widely used goodness-of-fit criteria that are not sensitive to sample size (Bentler and Bonett 1980): Incremental Fit Index (IFI) and Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI). These indices have expected values of 1.00 when the hypothesized

\(^6\) All values reported in tables refer to the arcsin transformed measure. Values for the untransformed measure were: mean = .16, s.d. = .16, range from 0 to .55. Within teams experiencing membership model divergence, mean (untransformed) membership model divergence was .22 (s.d. = .14). The correlation between the transformed and untransformed measures was .96.
model is true, and a value of .90 or higher suggests an adequate fit (Bentler and Bonett 1980). The values for all three within the saturated model indicated an excellent fit (IFI = .96, TLI = .94, and CFI = .96). Finally, I used the Root Mean Squared Error of Approximation (RMSEA), which is an estimate of the discrepancy between the original and reproduced covariance matrices in the population. A RMSEA of .08 or lower represents a reasonable fit and .05 or lower represents a good fit (Browne and Cudeck 1993). My saturated model yielded a RMSEA value of .06.

I tested three hypotheses predicting the proximate drivers of membership model divergence. Hypothesis 1a posits that the mean percentage of team members dedicated to their team will be negatively related to membership model divergence – the model path was significant and in the expected direction (β = −.30, p < .05). Hypotheses 1b and 1c posit that membership model divergence will be negatively related to teams’ average level of interaction, but positively related to heterogeneity in that interaction. Both hypotheses were supported, with level of interaction significantly negatively related to membership model divergence (β = −.51, p < .01), and heterogeneity in interaction significantly positively related to membership model divergence (β = .59, <01). Thus Hypotheses 1a-c are supported.

I tested five hypotheses predicting the conditions underlying the three proximate drivers of membership model divergence. Hypothesis 2a and 2b posit that multiple team membership and geographic distribution will both be negatively related to the percentage of time a team’s members spend on the team task. Both hypotheses were supported, as multiple team membership and geographic distribution were both significantly negatively related to percentage of time dedicated to the team task (β = −.30, p < .05 and β = −.46, p < .01 respectively). Hypotheses 2c and 2d posit that geographic distribution and team size will both be positively related to variance in a team’s interaction patterns. I found no significant relationship between geographic distribution and variance in a team’s interaction patterns (β = .09, n.s.), thereby failing to find support for Hypothesis 2c, but found team size was significantly positively related to team interaction pattern variance (β = .39, p < .05), supporting Hypothesis 2d. Finally, Hypothesis 2e posits that team size will also be negatively related to the mean level of interaction within a team. I found support for Hypothesis 2e, as team size was
significantly negatively related to mean level of interaction ($\beta = -0.37$, $p < 0.05$). Therefore Hypotheses 2a, b, d and e are supported.

Lastly, I tested two hypotheses regarding the effects of membership model divergence. Hypothesis 3a posits that membership model divergence will be negatively related to performance, and Hypothesis 3b that the relationship between membership model divergence and performance will be mediated by transactive memory effectiveness. To test Hypothesis 3a, I tested an alternative model identical to that presented in Figure 4, except for a direct path linking membership model divergence to performance and no measure of transactive memory. I found this model to be a good fit for the data, and that the path linking membership model divergence and performance was significant and negative ($\beta = -0.51$, $p < 0.01$), providing support for Hypothesis 3a. Introducing transactive memory into the model as a mediator resulted in significant paths between membership model divergence and transactive memory and from transactive memory to performance, while the direct path between membership model divergence was no longer significant ($\beta = -0.52$, $p < 0.01$; $\beta = 0.67$, $p < 0.01$; and $\beta = -0.18$, n.s. respectively), indicating full mediation. In the interest of clarity, Figure 4 presents the model without the non-significant direct path leading from membership model divergence to performance, but with the significant paths between membership model divergence and transactive memory ($\beta = -0.51$, $p < 0.01$) and between transactive memory and performance ($\beta = 0.77$, $p < 0.01$). Thus I find support for Hypotheses 3a and b.

**DISCUSSION**

With this study I provide the first systematic examination of membership model divergence, some of its antecedents and its effects. Occurring widely within the teams in my sample, membership model divergence was negatively related to the mean percentage of time that members spent in the team and the mean level of interaction in the team, and positively related to heterogeneity in team interaction patterns. Underlying these proximate drivers were structural characteristics of the team: multiple team membership and geographic distribution both reduced the amount of time team members dedicated to the focal team. Team size reduced per-person interaction, while increasing the variance within patterns of such interaction. Contrary to my hypothesis, I found no significant
relationship between geographic distribution and variance in interaction patterns. This may be due to the teams in my sample having well-established norms for communication – particularly cross-site interaction. Membership model divergence was in turn negatively related to perceptions of team performance as a result of reducing the effectiveness of the teams’ transactive memory systems. In all models, membership model divergence – as a latent variable – was more strongly associated with divergence between member models than between team member and team manager models, and negatively covaried with the extent to which members strongly identified with the team. These results confirm that membership model divergence, beyond simply reflecting a characteristic of the team, has a measurable effect on critical team dynamics and, ultimately, perceptions of performance. Furthermore, it appears that these effects occur primarily as a result of processes well established in the literature on teams – that is, by making it more difficult for teams to coordinate their cognitive processes.

**Implications for theory and contributions to key literatures**

As suggested in the introduction, membership model divergence has significant implications for how we understand the changing nature of work and the ways in which we have traditionally thought and theorized about teams. I discuss three such implications here, relating to the changing role of boundedness, differing conceptualizations of membership, and relating social psychological and social networks approaches to teams.

**The changing role of boundedness**

This study provides one of the most direct empirical explorations to date of the changing role of boundedness in teams. As noted, recent scholarly discussion has suggested that the traditional view of teams as bounded and stable is increasingly at odds with the ways in which teams are implemented and used in practice (e.g. Hackman and Katz 2010; Mortensen 2012). Specifically, scholars have noted that the boundaries of today’s teams are fluid, with members swapping in and out as needed (Grabher 2002; Prencipe and Tell 2001) as well as multiplex, with members inextricably connected to their organizational context (e.g. Hitt et al. 2007; Zaccaro et al. 2011) or to other teams directly (e.g. O’Leary et al. 2011a). Such fluidity and multiplexity results in boundaries that are both less clear and
more permeable than those characterized by existing theories (Mortensen 2012). While prior work has begun to explore some of these changes that affect team boundaries, the link to boundaries and the role and nature of boundedness remains largely unexplored. This study provides an important empirical examination of how one of the ways that changes to the design and implementation of teams are affecting boundedness – widely regarded as an important, if not definitional, attribute of teams.

This study also highlights the distinction between the team boundaries represented on organization charts and those perceived by team members. The idea that perceptions of reality shape behavior is pervasive (see, Berger and Luckmann 1966; Fiske and Taylor 2008; Jussim 1991; Pyszczynski et al. 2010), reflecting Thomas and Thomas’ widely-quoted statement that: “If men define situations as real, they are real in their consequences” (1928 p. 571). Less widely accepted is the notion that team behavior may be more heavily affected by socially-constructed perceptions of team boundaries than by the objective representations we see on organization charts. While scholars have recognized that psychological boundaries affect individuals’ actions and behaviors inasmuch as those individuals perceive and act as though they exist (e.g. Arrow et al. 2000; Weick 1979), most theories assume that team boundaries are unambiguous, agreed upon, and match the officially sanctioned versions provided by management (Diehl 1990). The existence of membership model divergence, however, suggests that this assumption is incorrect.

Recognizing this discrepancy is critical, as many of our theories of team dynamics are driven more directly by a team’s perceptions of its boundaries than by how those boundaries are objectively defined on organization charts. Theories of social categorization and identification, for example, argue that identifying with a group affects both intra- and inter-group attitudes and behaviors (Ashforth and Mael 1989; Hogg and Terry 2000). Importantly, it is individuals’ perceptions that they are members that drives categorization and identification effects – not their membership according to official rosters. By directly exploring the drivers and consequences of perceptions of membership within the small-scale work teams for which our theories assume membership is unambiguous and agreed upon,
this study underscores the need to pay attention not only to officially-sanctioned membership but to perceptions of membership as well.

The relationship between perceived and official membership is made more complex because members frequently do not recognize the distinction between the two. In post-survey interviews, respondents all considered themselves to be team members and generally assumed membership to be agreed upon. This was the case irrespective of the level of membership model divergence that teams actually reported. These seemingly contradictory stances highlight the complex relationship between the objective definition of a team and the subjective understanding of it.

Despite these difficulties, exploring this distinction in greater depth stands to improve our understanding of well-established theoretical constructs. The literature on entitativity, for example, asserts that team members’s perceptions will be affected by the extent to which a team feels like it is an intact “entitative” unit. While research has found significant variations in levels of entitativity across teams (Hamilton et al. 1998; Lickel et al. 2000), it is assumed that this variation occurs even though members hold the same basic model of the team. Recognizing that teams frequently do not agree on their membership is an important insight for scholars of entitativity as it suggests that members of a team may perceive and report that a team is highly entitative while not recognizing that they are evaluating different models of the same team. It is reasonable to assume that membership model divergence is a key – albeit unexplored – antecedent of entitativity. To the extent that the members of a team differ in their models of the team itself, they are likely to perceive the behaviors they see as less entitative. This points to a potential line for future research: exploring the link between individuals’ perceptions of supposedly objective structural team characteristics and their subjective relationships with those teams.

**Linking different approaches to defining and studying teams**

Building on the above arguments, membership model divergence also suggests a way to think about the relationship between two approaches to studying, thinking about, and defining teams – those found in social network analysis and social psychology.
Social networks research approaches groups primarily as emergent structural characteristics of social networks, identified on the basis of relative tie strength and density. Scholars of social networks often treat groups as an emergent pattern of relationships without considering the goals, tasks or other factors that may shape the pattern of relationships that results in an identifiable group. In many studies based in social network analyses, (see, for example, Cummings and Cross 2003; Reagans and Zuckerman 2001; Sparrowe et al. 2001), teams are frequently seen as a context rather than a phenomenon that affects the attitudes and behavior of members.

In contrast, social psychologists have traditionally approached groups from the opposite end – defining them solely on the basis of those attitudes and behaviors and not at all on the basis of the actual structural characteristics they manifest. For many social psychological theories, the most important feature of a group is a set of core attributes represented in an actor’s mind rather than a list of names on a roster or as calculated through an algorithm. Within the large body of research on identification and social categorization, for example, the key driver of categorization effects is not actual inclusion on team rosters, but the identification of a target with a given group (Abrams and Hogg 1990). Such research focuses on individuals’ perceptions of (and reactions to) an abstraction tied to a set of shared values, goals, beliefs and perspectives. By incorporating both the patterns of interconnection among team members (based on membership attributions) and team members’ perceptions of the team (based on an abstract mental representation), membership model divergence provides a link between the social network and social psychological perspectives. From a traditional social network approach, the discord between higher-level abstractions brought about by variations in structure is lost; conversely when taking a traditional social psychological view of the team, differing structures and conceptualizations underlying similarly named abstract team identities are not likely to be detected. In this way, research on membership model divergence brings the abstraction of a team to social networks, and a concrete grounding in patterns of interpersonal interactions to social psychology.

This study demonstrates how phenomena such as membership model divergence may exist and thrive at the intersection between these approaches to conceptualizing and studying teams.
Furthermore, it illustrates the importance of concurrently exploring and comparing multiple approaches to thinking about teams as a means of fully understanding them. More broadly, by recognizing that members’ models of membership are subjectively based on their experiences, and that such models shape their behavior, we may need to reassess our definition of the team, shifting to a model that incorporates both objective patterns of relationships and subjective perceptions of an entitative abstraction. In this way, membership model divergence provides a link between the social networks approach and the social psychology approach to groups, as well as illustrating the benefits of rethinking how we conceptualize teams.

**Implications for methodology**

The existence of membership model divergence and the contextual changes that nurture it suggest important methodological considerations that have been missing from previous work. Furthermore, the results of this study suggest that the methodological approaches of prior work may unwittingly have affected scholars’ ability to recognize and account for membership model divergence. Lacking a conceptual and empirical approach to account for membership model divergence, prior research has either been unable to capture and accurately interpret it when it has occurred, or unintentionally constrained it – both with serious implications.

In some cases, study design has unintentionally eliminated membership model divergence, as in the case of experimental settings in which random assignment to short-term in-lab groups artificially eliminates membership model divergence, or field studies in which membership is explicitly delineated by researchers by providing respondents with membership lists they have no opportunity to validate (e.g., Ancona and Caldwell 1992a). Such designs have eliminated membership model divergence, with significant – and to date unexamined – consequences on the external validity and generalizability of their findings. Looking towards the future, eliminating membership model divergence is not in itself a bad methodological step, given the complexity of the phenomenon and the fact that it is likely to be difficult to accurately replicate in laboratory settings. However, in such situations, membership model convergence should be explicitly identified as a simplifying assumption. Importantly, when using the findings of such studies to understand teams in the field, we
must explicitly consider the effects of relaxing that simplifying assumption and ask how the existence of membership model divergence will affect the observed and predicted relationships.

In other cases, membership model divergence has occurred in our studies but has either gone unrecognized (e.g., studies in which team members’ representations of their teams were not captured) or mis-identified as an artifact of the study design (e.g., studies in which membership model divergence was identified as measurement or recall error) and discarded. Both scenarios leave scholars unable to disentangle the mediating or moderating effects of membership model divergence from the other phenomena of interest in the teams under study. Looking to future studies, this suggests the importance of explicitly considering whether there is a reasonable expectation that a study’s focal phenomena are either covariates (e.g., entitativity or identification) or consequences (e.g., transactive memory) of membership model divergence. When such links exist, we must capture and explicitly examine the links between such phenomena and membership model divergence or identify boundary conditions delimiting its relevance.

**Implications for practice**

This study identifies a number of negative consequences of membership model divergence on team processes (e.g., transactive memory) and outcomes (e.g., performance). As noted in the introduction, because membership models underlie the formation and maintenance of other mental models, any of these potential negative implications are likely to be reinforced and magnified through the increasing misalignment between a team’s mental models of other factors. Given these negative consequences for important team-level outcomes, it may be tempting to conclude that managers and members should strive to reduce membership model divergence.

Before jumping to that conclusion, however, we should recognize that these negative effects may arise not from divergence itself – members holding different models of the team – but from their being *unaware* that their models of the team’s membership differ. By focusing on *agreement*, managers are likely to seek to reduce membership model divergence, for example, by increasing member interaction and information (e.g., increasing time spent on the team or promoting communication among team members). In this way they might work to “clarify” membership and
increase alignment around a single model (e.g., that published in team rosters or instantiated in technologies like information systems). In contrast, by focusing on awareness they are likely to encourage team members to share their differing models. This would mitigate some of the negative consequences of membership model divergence. Conversely, it might also allow a team to leverage its potential benefits, e.g., as a potential source of cognitive diversity and creativity. In addition, it might reduce the significant effort and coordination required to ensure team members continue to hold the same mental model, especially amidst fluidly shifting project-based work. Armed with the knowledge that membership model divergence may be occurring, team members and managers may be able to assess and discount any confusion or disagreement that could arise from members working with differing underlying perceptions of the team. In theory, this would allow teams to break the cycle whereby it establishes and reinforces divergence in other mental models. The relative merits of an agreement vs. awareness approach, and the ability of such tactics to break the cycle of reinforcement, however, deserves empirical investigation.

**Future research**

By providing evidence of its links to well-studied antecedents and outcomes, this study establishes membership model divergence as an important construct to be theoretically and empirically accounted for in future research. As with most initial explorations of a phenomena, the answers to the research questions underlying this study give rise to an even larger number of questions to be addressed in future research. Rather than an exhaustive list, I identify a small number of areas for future research with particularly interesting theoretical or empirical consequences for our understanding of membership model divergence and perceptions of membership more broadly.

**Membership model divergence – Additional antecedents, consequences, and mechanisms**

This study explores how team level factors affect the data used by teams to create their membership models and how divergence in those models subsequently affects cognitive processes and ultimately performance. The model presented and tested here reflects design choices that necessarily limit its scope and preclude the testing of a complete model of all the antecedents and effects of membership model divergence suggested by existing theory. While listing the additional
factors suggested by existing theory is infeasible, as an illustration I highlight two which I consider particularly interesting.

First, there are a number of antecedents of membership model divergence that are likely to shape membership models, not through affecting the data that teams base their models on but by shaping how they interpret that data. These might occur as the result of the aggregation of individual-level factors, as in the case of individual psychological biases (e.g., anchoring, clustering, or exposure effects) that affect each team member’s information processing; or at the level of the team itself (e.g., false consensus, outgroup homogeneity, or system justification). One particularly unique and interesting mechanism affecting interpretation is intentionality, as in situations in which a team chooses to attribute or deny membership as a way of giving or withholding the prestige associated with membership. Though it may appear qualitatively different, this can be seen as a factor affecting the interpretation of membership data with the goal of manipulating the resultant team membership.

Second, whereas I have focused on performance framed in large part around the quality and quantity of output produced by teams, Hackman and others argue that overall team effectiveness should be assessed not only in terms of team output, but also in terms of individual team members’ learning and development, as well as their ability to work together again in the future (Hackman 1987, 2002). Though not modeled in this study, existing research and theory gives us reason to believe that both are likely to be affected by membership model divergence. Research on learning, for example, consistently finds that variation in context and membership is a key source of new ideas (Argote 1993; Edmondson 2002). Membership model divergence means, in effect, that team members focus on differing groups of individuals as sources of information, which may in fact stimulate learning, in line with the findings of Gibson and Vermeulen, who concluded that subgroups promoted learning within teams (2003). In contrast, the negative social dynamics discussed earlier (e.g., increased role ambiguity and conflict, and reduced clarity of norms and trust) may negatively impact teams ability to learn, as suggested by recent work by Bresman and Zellmer-Bruhn (2012) which finds that highly structured teams (with high role clarity) learn more because they are more psychologically safe. As one might expect membership model divergence and role clarity to be inversely related, this suggests
a contrary effect whereby membership model divergence may negatively relate to learning through its effects on psychological safety. Negative social dynamics within teams experiencing membership model divergence may also make it more difficult for team members to work together again in the future – either in the same team or recombined into different teams. Thus, though the net effect of membership model divergence on team effectiveness remains unclear, it is likely that it differentially affects the distinct elements of team effectiveness.

Membership model divergence – Links to other types of mental models

In exploring membership model divergence, this study has begun to illustrate some of the unique issues that arise when a team’s members do not share the same underlying model of the team itself, building substantially on the large body of research on shared mental models. One particularly interesting domain for future research is the interaction between membership model divergence and unshared mental models of other phenomena. I have argued that to the extent that members of a team do not hold a shared model of the team’s membership, it is unlikely that the team will hold shared mental models of other factors as well. This implies that divergence in membership models holds a unique position as both having its own effects as well as additional effects through other unshared mental models. Still unexplored are the mechanisms through which membership models specifically shape mental models of other phenomena. This calls for further exploration of relationships and feedback loops with other such models which might serve to reinforce or dampen its effects. As these are empirical questions, further exploration of these mechanisms is needed to allow us to better understand the cumulative effects of membership model divergence, as well as the potential reinforcement, concentration and magnification of its effects through other mental models.

Membership model divergence – Structure and temporality

As an initial exploration of membership model divergence, this study focuses on its most basic core aspects – if and how much it occurs. It does not examine the structure of the resultant membership models and divergence among them. Other scholars, however, have made a strong case that different structures have substantial effects on groups (Guimerà et al. 2005; Rulke and Galaskiewicz 2000). For example, research on core/periphery structures (Borgatti and Everett 1999)
found that groups frequently had certain “core” members who were well connected to the rest of the team, and “peripheral” members who were less connected. In the case of membership model divergence, particularly as we find it to be driven in part by patterns of interaction, we would expect certain individuals to be included in the membership models of most, or all, of their teammates, and others to be included only in the membership models of a small subset of individuals with whom they interact significantly. Similarly, cliques of relatively highly-interconnected actors exist in most networks (Alba 1973), often leading to the formation of subgroups within teams which have significant team-level effects (Gibson and Vermuelen 2003; O'Leary and Mortensen 2010). It seems reasonable to assume that membership models form clusters within a team, with individuals including one another more within than across clusters. While not captured in the measure of membership model divergence used here, this suggests membership model structure may also have a significant effect on team-level outcomes, meriting further study.

This prompts a related set of questions related to how the mental models of a team’s members both shape, and are shaped by, interactions in an ongoing cycle (Marks et al. 2001). A team’s pattern of relationships shapes its members’ perceptions of the team, which then influences future relationships. Given the structural arguments suggested above, this might lead to varying outcomes depending on the initial membership model structure. In some cases this feedback loop may lead to a more tightly bounded and defined team over time, while in others it may increase fragmentation. This suggests that not only exploring structure, but also how such structures impact the way membership model divergence shifts over time is an important avenue for future research.

**Thinking about membership – Different bases**

The recognition of membership model divergence also suggests the need for further research to examine how we think about and understand membership both as scholars and practitioners. As outlined in the introduction, individuals rely on a combination of three different approaches to determining membership – they may determine their models of membership based on who is officially named as a member of the team, whom they identify with the team, and with whom they interact most for team-related tasks (formal, identified, and emergent respectively). Membership
model divergence occurs when two or more of these approaches to membership fail to yield a shared model, or when multiple members reach different models based on the same approach, making it extremely tricky to identify and fully understand all the drivers of membership model divergence. Further examination of the factors shaping team members’ reliance on one or more of these approaches (over another) is an important next step if we wish to improve the accuracy of our predictions of when membership model divergence will occur and what it will look like. Also worth considering here is the so far unexplored role of intentionality as might be the case in situations in which a team might choose attribute or deny membership as a way of giving or withholding the prestige associated with membership.

Conclusion

Team membership has long been considered one of the most basic and powerful drivers of a team’s behavior, dynamics and outcomes. With this study I suggest that membership may not be as clear as previously assumed in both theory and practice. Seen against a backdrop of a shift towards more fluid and multiplex teams, the possibility of a team’s members disagreeing on its composition cannot be ignored and must be taken into account in the design and implementation of future teams. By showing that membership model divergence occurs and drives important dynamics and outcomes, I seek to fill a gap in our understanding outlined by Guzzo and Dickson in their call for research “to clarify issues of inclusion and exclusion by virtue of team boundaries, how boundaries relate to effectiveness, and how the nature of boundaries might shape the effects of interventions intended to raise team performance” (1996 p. 332). Membership model divergence arises from the complex relationship between people and the teams to which they belong, and the findings presented here highlight the need for additional research into the often overlooked domain of team membership – what it is, where it comes from, and what it does.
REFERENCES


Ellis, A. 2006. System breakdown: The role of mental models and transactive memory in the relationship between acute stress and team performance. *Acad. of Management J.*


<table>
<thead>
<tr>
<th></th>
<th>How is membership defined?</th>
<th>What is the conceptual focus?</th>
<th>Who attributes membership and through what mechanism?</th>
<th>Where is this conceptualization found?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Formal</strong></td>
<td>People included in “official” organizationally-provided team roster</td>
<td>How the organization defines the team</td>
<td>Organization (or representative thereof) through formal assignment</td>
<td>Organizational behavior research on groups and teams in the field (e.g. Barker 1993) and laboratory experiments (e.g. Wittenbaum et al. 1996)</td>
</tr>
<tr>
<td><strong>Identified</strong></td>
<td>People who identified as team members (by themselves or other team members)</td>
<td>How individuals think of and categorize themselves and others</td>
<td>Self or peers through individual attribution</td>
<td>Social psychological research based in identification (e.g. Hogg 2001; Tajfel and Turner 1986)</td>
</tr>
<tr>
<td><strong>Emergent</strong></td>
<td>People whose patterns of relationships identify them as a team</td>
<td>Naturally occurring groups that may or may not be recognized</td>
<td>Network (as shaped by actors) through pattern emergence</td>
<td>Social network research on cliques (e.g. Falzon 2000) and informal organizational structures (e.g. Krackhardt 1994)</td>
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Table 2: Descriptive statistics and correlations between key variables

<table>
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<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
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</thead>
<tbody>
<tr>
<td>1 Inter-Member MMD</td>
<td>0.69</td>
<td>0.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Member-Manager MMD</td>
<td>0.81</td>
<td>0.53</td>
<td>0.54**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3 Multiple Team Membership</td>
<td>1.98</td>
<td>0.69</td>
<td>0.00</td>
<td>0.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>4 Geographic Distribution</td>
<td>0.71</td>
<td>0.46</td>
<td>0.17</td>
<td>0.32*</td>
<td>0.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>5 Team Size</td>
<td>16.45</td>
<td>8.83</td>
<td>0.53**</td>
<td>0.24</td>
<td>-0.11</td>
<td>0.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>6 Percentage of Time Dedicated to Team</td>
<td>78.89</td>
<td>17.18</td>
<td>-0.37*</td>
<td>-0.44**</td>
<td>-0.36*</td>
<td>-0.50**</td>
<td>-0.03</td>
<td></td>
<td></td>
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<td>7 Interaction (Variance)</td>
<td>29.99</td>
<td>37.68</td>
<td>0.29</td>
<td>0.09</td>
<td>-0.11</td>
<td>-0.01</td>
<td>0.39*</td>
<td>0.06</td>
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<td>8 Interaction (Mean)</td>
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<td>0.32</td>
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<td>-0.20</td>
<td>-0.10</td>
<td>-0.19</td>
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<td>0.29</td>
<td>0.43**</td>
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<td>9 Identification</td>
<td>3.86</td>
<td>0.42</td>
<td>-0.38*</td>
<td>-0.34*</td>
<td>-0.14</td>
<td>-0.31</td>
<td>-0.04</td>
<td>0.26</td>
<td>-0.08</td>
<td>-0.01</td>
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<tr>
<td>10 Transactive Memory</td>
<td>3.81</td>
<td>0.29</td>
<td>-0.31</td>
<td>-0.22</td>
<td>-0.10</td>
<td>-0.11</td>
<td>-0.23</td>
<td>0.16</td>
<td>-0.26</td>
<td>-0.02</td>
<td>0.59**</td>
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<td>11 Performance</td>
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<td>0.10</td>
<td>0.09</td>
<td>0.15</td>
<td>0.12</td>
<td>-0.16</td>
<td>0.01</td>
<td>-0.18</td>
<td>-0.04</td>
<td>0.16</td>
<td>0.35*</td>
</tr>
</tbody>
</table>

* p < .05, ** p < .01
FIGURES

Figure 1: Approaches to modeling membership

Note: Shading represents overlap in an individual’s membership models; darker indicates convergence and lighter represents divergence in membership models.
Figure 2: Model of Relationships
Figure 3: Membership model divergence calculation example

**Membership Models**

<table>
<thead>
<tr>
<th>Source</th>
<th>Members</th>
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<tbody>
<tr>
<td>Roster</td>
<td>Abe Beth Chris Dan</td>
</tr>
<tr>
<td>Abe</td>
<td>Abe Beth Chris Dan</td>
</tr>
<tr>
<td>Beth</td>
<td>Abe Beth Chris Ella</td>
</tr>
<tr>
<td>Chris</td>
<td>Beth Chris Dan</td>
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**Membership Model Divergence Calculation**

<table>
<thead>
<tr>
<th>Source</th>
<th>Abe</th>
<th>Beth</th>
</tr>
</thead>
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<tr>
<td>Roster</td>
<td>1/4=.25</td>
<td>1/4=.25</td>
</tr>
<tr>
<td>Abe</td>
<td>1/4=.25</td>
<td>2/5=.40</td>
</tr>
<tr>
<td>Beth</td>
<td>2/4=.50</td>
<td>1/4=.25</td>
</tr>
<tr>
<td>Chris</td>
<td>3/5=.60</td>
<td></td>
</tr>
</tbody>
</table>

\[
MMD_{NM} = 0.33 \\
MMD_{IM} = 0.42
\]
Figure 4: SEM of membership model divergence