A PROCESSUAL THEORY OF STRATEGIC CONSENSUS

by

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(Under the Direction of Dorothy R. Carter)

ABSTRACT

Strategic consensus — i.e., “shared understanding of strategic priorities among managers at the top, middle, and/or operating levels of the organization” (Kellermanns et al. 2005, p. 721) -- is considered essential to organizational performance. Unfortunately, organizations often struggle to develop strategic consensus; managers’ perceptions regarding strategic priorities often become *polarized* (i.e., two distinct subgroups with differing opinions) or *fragmented* (i.e., multiple subgroups with varying opinions) leading subgroups to work at cross-purposes toward different priorities. Therefore, understanding the antecedents of strategic consensus (i.e., *why* and *how* does strategic consensus emerge?) is an important goal for organizational research. Conceptual work on strategic consensus depicts the phenomenon as complex and dynamic -- ‘emerging’ over time through networked social interaction processes among managers at multiple organizational levels. However, prior empirical research on strategic consensus has typically depicted the phenomenon as a static one-time event (using cross-sectional data) and focused almost exclusively on top-down antecedents such as the attributes or behaviors of senior leaders or the formal organizational structure. In contrast to prior work, this dissertation aims to advance knowledge surrounding the antecedents of strategic consensus by modeling the dynamic *micro-level* interaction processes among upper- and middle-level managers that give rise to macro-level emergent patterns of strategy perceptions. I began by leveraging theories of organizational social networks, top management team dynamics, and social influence to articulate a series of ‘tendencies’ or ‘rules’ governing micro-level interaction processes that are especially relevant to strategic consensus. Then, I translated this ‘verbal theory’ into a formal (mathematical) theory which I implemented as an agent-based computational model. I verified and validated the formal theory using perceptual self-report and social network data from the upper- and middle-level managers within three organizations. Lastly, I conducted a series of virtual experiments to examine two preliminary research questions considering the impact of communication network structure and influence on the patterns of strategic priority perceptions that are likely to arise within an organizational system. Ultimately, the results of this dissertation provide initial insights into the dynamics of strategic consensus emergence and suggest multiple avenues for future research.

INDEX WORDS: Strategic consensus, Computational model, Strategy

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CHAPTER 1

INTRODUCTION

Our goals can only be reached through a vehicle of a plan, in which we must fervently believe, and upon which we must vigorously act. There is no other route to success.

- Pablo Picasso

Strategic consensus, defined as the "shared understanding of strategic priorities among managers at the top, middle, and/or operating levels of the organization" (Kellermanns et al. 2005, p. 721), is essential to organizational functioning and success. Strategic consensus can foster commitment to organizational strategy, coordination and collaboration, and more efficient strategic decision-making (Bourgeois & Eisenhardt, 1988; Eisenhardt, 1989; Gonzalez-Benito et al., 2012; Homburg et al., 1999). Moreover, establishing strategic consensus is increasingly relevant to organizational performance given the unprecedented challenges and disruptions (e.g., globalization, technological advancements, competition; Siggelkow & Rivkin, 2005; pandemics; Nyberg et al., 2021) that are requiring leaders to quickly assess new situations and establish new strategies and sets of priorities (Carrington et al., 2019).

Given the importance of strategic consensus to organizational functioning and performance, organizational researchers have sought to understand *why* and *how* strategic consensus arises across organizational levels. The literature has identified at least three key categories of strategic consensus antecedents: (1) *individual attributes* of top-management team (TMT) members (e.g., age, experience, or functional background; Dess & Priem, 1995; Iaquinto

& Fredrickson, 1997; Knight et al., 1999; Michel & Hambrick, 1988; Priem, 1990); (2) *interaction and/or decision-making processes* (e.g., increased communication between the TMT and middle-level management; Rapert et al., 2002; cognitive conflict; Amason, 1996; involvement of middle-level managers in strategy; Wooldridge & Floyd, 1990; agreement seeking behaviors; Knight et al., 1990); and (3) the overall *organizational structure* (e.g., centralization; Bourgeois & Eisenhardt, 1988; Dess & Priem, 1995; Eisenhardt & Bourgeois,1988; formalization; Menon et al., 1999; Priem, 1990; hierarchical differentiation; Priem, 1990; task specialization; Welsh & Slusher, 1986).

However, prior empirical research on the antecedents of strategic consensus is limited in several ways. First, although strategic consensus is conceptualized as a *dynamic* phenomenon (e.g., managers converging on shared priorities over time), prior empirical research has predominantly investigated cross-sectional patterns of covariation between the antecedents and outcomes of strategic consensus (Kellermans et al., 2005). Second, studies of strategic consensus have often adopted a *'top-down'* view of the phenomenon by focusing on predicting consensus within the TMT or on how top-down interventions (e.g., leader behavior) shape strategic consensus at lower managerial levels. Yet, scholars are increasingly recognizing that middle-level managers take an active role in shaping strategy development and implementation (Raes et al., 2011). As Kellermans and colleagues (2011) emphasize, "if consensus is conceptualized as agreement on strategic priorities at middle and lower levels of management, the degree of middle-management involvement in the decision process and the structure of the organization (e.g., the level of decentralization) are likely to offer better explanations of how and whether consensus develops" (p. 731). Third, although strategic consensus is thought to exist within the minds of managers and arise through micro-level processes of communication within and across managerial groups, it has typically been investigated from a macro-organizational perspective which does not elucidate the micro-level (individual, relational) processes that ultimately give rise to the construct. Fourth, the studies that *have* attempted to consider micro-level interaction processes, such as communication, have typically assumed that participation in these processes is *equal* across managers (Kellermanns et al., 2005, 2011; Markoczy, 2001; Tarakci, 2014). However, research on organizational communication networks has repeatedly demonstrated that certain employees in organizations are more connected or involved in communication processes than others (i.e., popularity; Balkundi, Barsness, & Michael, 2009; Park et al., 2020), people tend to communicate more often with others who are similar to themselves (i.e., homophily; Brass et al., 2004; McPherson et al., 2001; Monge & Contractor, 2003), and people are more willing to accept influence from those whom they trust (Martins, 2013; Wells & Kipnis, 2001). Notably, the limitations of prior research are understandable given the complex and dynamic nature of the phenomena, as well as the prohibitive nature of collecting relevant data from a sufficient number of organizations.

The purpose of this dissertation is to advance understanding of how and why strategic consensus emerges by modeling the dynamic *micro-level* interaction processes among upper- and middle-level managers that give rise to macro-level patterns of strategic priority perceptions. Toward that end, this dissertation: (1) develops a formalized theory that articulates the networked micro-processes through which managers impact one another's strategic priority perceptions and (2) evaluates this theory using an agent-based computational modeling approach combined with self-report perceptual data drawn from three organizations. Computational modeling is an especially appropriate tool for studying strategic consensus emergence because this approach allows researchers to investigate populations, events, and/or phenomena that have been traditionally guarded by practical barriers. Further, computational models afford the opportunity to specify theory with great precision, as interaction rules and individual behaviors must be specified verbally, mathematically, and programmatically (Grand et al., 2016; Guest & Martin, 2021; Harrison et al., 2007).

In **Chapter 2**, I review the literature on strategic consensus paying particular attention to prior research on antecedents. Then, in **Chapter 3**, I leverage theories of organizational social networks, top management team dynamics, and social influence to advance a 'verbal theory' which argues that strategic priority perceptions develop in the minds of top- and middle-level managers and are shaped by communication processes that operate through both formal and informal social network channels. In **Chapter 4**, I translate the verbal theory into a formal (mathematical) theory that formally specifies the nature of the interactions and processes that occur among organizational leaders as outlined in the verbal theory. **Chapter 5** provides a detailed summary of the characteristics of the empirical data collected from top- and middle-level managers within three organizations that I used to parameterize and validate the agent-based model. **Chapter 6** describes the results of validation analyses which provide support for the proposed model. **Chapter 7** presents the results of virtual experiments addressing two initial Research Questions: (RQ1): What is the impact of initial communication network structures (i.e., communication centralization and density within and across component groups) on emergent patterns of strategic priority perceptions? (RQ2): What impact do influential individuals have on eventual patterns of strategic priority perceptions? **Chapter 8** provides a general discussion of this project. Ultimately, the results of this dissertation provide initial insights into the dynamic nature of strategic consensus among organizational leaders and generate numerous avenues for future research.

CHAPTER 2

A REVIEW OF STRATEGIC CONSENSUS RESEARCH

Defining Strategic Consensus

Strategic consensus is defined as agreement on strategic priorities among managers at various levels of the organizational hierarchy (Floyd & Wooldridge, 1992; F. Kellermanns et al., 2005; F. W. Kellermanns & Floyd, 2005; Wooldridge & Floyd, 1989, 1990). Wooldridge & Floyd (1989) identified three dimensions of strategic consensus: *degree, scope, and content.* Degree refers to the *amount* of consensus in the organization across people. For example, an organization has a higher degree of consensus when many individuals and/or groups are highly aligned in their views of strategic priorities. Scope refers to the *extent* to which strategic consensus spans multiple groups, such as the TMT, middle management, or production-level managers. Content refers to *what* is being agreed upon, such as organizational goals or the plans to achieve them (e.g., means vs. ends). Markoczy (2001) expanded upon these dimensions, suggesting that the *locus* of consensus is also a valuable characteristic for understanding strategic consensus. Locus refers to *where* consensus originates within the organization, highlighting the potential for individuals and groups outside of the TMT to influence the strategic process. Indeed, strategy development and implementation often requires coordination between multiple groups across organizational levels (Porck et al., 2020; Porck & van Knippenberg, 2022; Tarakci et al., 2014)

Outcomes of Strategic Consensus

Strategic consensus has become an important construct in the strategic management literature due to its relationship with organizational performance (Homburg et al., 1999; Iaquinto & Fredrickson, 1997; Joshi et al., 2003; F. Kellermanns et al., 2011; West & Schwenk, 1996). Strategic consensus helps to explain the strategic process, or how strategy is developed, disseminated, and implemented to ultimately drive organizations towards their objectives. Arguably, even if effective strategies are developed, they will not be successful unless they are implemented appropriately, and implementation often depends on consensus (Amason, 1996; Noble, 1999). As such, strategic consensus has been linked to organizational performance through its influence on the effectiveness of strategy implementation (Aggarwal & Woolley, 2013; Dess & Origer, 1987; Homburg et al., 1999; Roberto, 2004).

Researchers have further articulated *how* strategic consensus fosters strategy implementation effectiveness (i.e., the explanatory mechanisms). For instance, Child (1972) proposed that agreement on strategic priorities is critical for organizational performance because: (1) strategies guide the decisions and behaviors of individual leaders; (2) pursuing multiple conflicting priorities is inefficient; and (3) discordant views of strategic priorities can cause conflict, reducing collective efforts towards organizational objectives. Researchers have also suggested that strategic consensus positively influences strategy implementation because consensus enhances commitment to strategy (Dess & Priem, 1995; Dooley et al., 2000). Strategic commitment reflects an individual's willingness to invest resources into a strategy. Managers become more committed to strategy when they perceive that it aligns with the interests of the organization and their personal interests (Floyd & Wooldridge, 1992). Ultimately, commitment means that one is willing to expend more energy towards the implementation of particular strategies, and has a vested interest in their success.

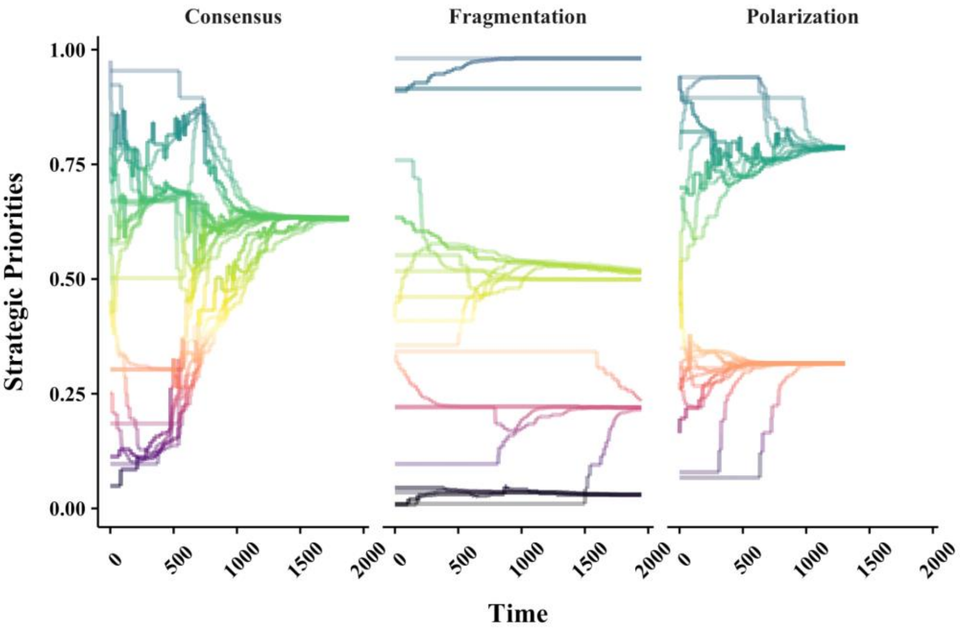
The importance of strategic consensus in macro-level organizational research is also consistent with micro- or meso-level research on small groups and teams which has provided extensive evidence demonstrating that cognition is one of the main drivers of effective team behaviors (DeChurch & Mesmer-Magnus, 2010). The cognitions that occur within teams and small groups are often referred to as schemas or mental models. Mental models are cognitive maps consisting of complex relationships between related concepts. Mental models are used in order to describe, explain, and predict aspects of the environment (Klimoski & Mohammed, 1994). Importantly, when two or more people hold a similar mental model, they perceive, explain, and predict their environment more similarly, leading to similar patterns of decision-making and behavior (F. W. Kellermanns et al., 2008; Mathieu et al., 2000). Indeed, research shows that consensus-building conversations lead to the development of aligned patterns of brain activity (Baek et al., 2022; Sievers et al., 2020).

Leveraging the language of small groups research, strategic consensus can be conceptualized as a ‘shared mental model’ regarding strategic priorities (Knight et al., 1999; Murase et al., 2012; Wildman et al., 2014). Indeed, parallelling research on small teams, managers who have developed a shared strategic mental model are better able to coordinate their efforts, working in a unified manner to implement strategic priorities (Aggarwal & Woolley, 2013). Managers who agree on strategic priorities may more effectively anticipate the actions of others, manage interdependencies, communicate, and adapt to changing circumstances (Bourgeois, 1980; Wang et al., 2019). Strategic consensus can also support coordination, communication, and collaboration by reducing errors caused by miscommunication and misalignment (Aggarwal & Woolley, 2013).

Unfortunately, many organizations struggle to elicit strategic consensus. Instead, perceptions of strategic priorities often become *polarized* (i.e., two distinct subgroups with differing opinions) or *fragmented* (i.e., multiple subgroups with varying opinions) leading managerial groups to pursue incompatible goals and suffer from communication and coordination failures. Figure 2.1 illustrates the emergence of these three different patterns of strategic priority perceptions over time. The lines in Figure 2.1 represent the managers within an organization; the colors indicate managers' perceptions of strategic priorities. The left-hand panel illustrates the emergence of strategic consensus -- although the managers held different perceptions of strategic priorities initially, their perceptions converged over time as indicated by the convergence of all lines toward the 'green' line in the center of the diagram. In contrast, the middle panel of Figure 2.1 illustrates the emergence of a 'fragmented' pattern such that different managerial subgroups continued to hold different perceptions regarding strategic priorities over time. The right-hand panel illustrates the emergence of 'polarization' such that two separate subgroups emerged over time with different perceptions regarding strategic priorities.

Figure 2.1

Archetypal Patterns of Strategic Priority Perceptions



Note: Strategic priority perceptions are represented by a continuous value (0, 1). Initial strategic priority perceptions for each individual are randomly selected from the open unit interval (0, 1). Each line represents the evolution of one individual's strategic priority perceptions. Colors represent individuals' strategic priority perceptions at each time point.

Antecedents of Strategic Consensus

Given the importance of developing strategic consensus (as opposed to polarization or fragmentation), researchers have increasingly sought to better understand why and how strategic consensus emerges. The literature on strategic consensus identifies three key categories of antecedents: (1) individual attributes (e.g., TMT member demographics); (2) interaction processes (e.g., communication, conflict, etc.); and (3) organizational characteristics (e.g., centralization, task differentiation etc.).

For example, research on the antecedents of strategic consensus has focused on TMT member attributes such as *demographic homogeneity* (Dess & Priem, 1995; Knight et al., 1999;

Priem, 1990; West & Schwenk, 1996). The idea that demographic homogeneity leads to shared cognitions is based on upper echelons theory which proposes that the demographic characteristics of organizational leaders influence their cognition and decision-making. As such, it is suggested that leaders who have similar characteristics and/or experiences will have similar mental representations and therefore will perceive strategic priorities similarly (Hambrick & Mason, 1984; Knight et al., 1999).

Expanding beyond individual attributes, scholars have emphasized that strategic consensus arises through a variety of *interaction processes.* For instance, in a study of leaders in the healthcare industry, Rapert et al. (2002) found that vertical communication between TMT members and middle managers was positively related to strategic consensus. Specifically, consensus was fostered by TMT members communicating with leaders throughout the organization to develop a shared understanding of the organizational environment and the rationale behind strategic priorities. Knight et al., (1999) found that interpersonal conflict amongst TMT members in technology firms led to decreased consensus, while agreement-seeking behaviors led to increased similarity in leader perceptions of strategic priorities. Interventions targeted at improving interaction processes that foster consensus have also been examined. For example, St. John & Rue (1991) investigated the role of coordinating mechanisms in the development of inter-departmental strategic consensus, finding that the frequency of such mechanisms was positively related to consensus. Other scholars have emphasized the role of *middle managers* in the development of strategic consensus and the importance of goal alignment across the levels of organizations. For instance, Wooldridge and Floyd (1990) proposed that involving middle managers in the development of strategy ensures that strategic implementation is aligned with the TMT's strategic priorities, fostering middle manager commitment to strategy and improving implementation. Similarly, the work of Pappas et al. (2003), suggested that strategic consensus can be fostered by middle managers having an understanding of the external environment as well as the organization's internal resources and capabilities.

Finally, *formal organizational structures* may be essential precursors to strategic consensus. For instance, Wooldridge and Floyd (1990) provided evidence suggesting that centralized organizations may better foster strategic consensus as there are fewer people involved in decision making and less of an opportunity for divergent perspectives. Welsh and Slusher (1986) examined task interdependence among employees as a moderator of the relationship between strategic consensus and political activity. When interdependence was high, employees with high consensus exhibited less political activity, ostensibly allowing a coalition to be maintained; but when interdependence was low, employees with high consensus exhibited more political activity, potentially assisting the formation of new coalitions.

Limitations of Prior Research on Strategic Consensus Antecedents

Despite significant efforts to understand the antecedents of strategic consensus, there remain important limitations to our understanding of consensus. Chief among these limitations is that strategic consensus has typically been examined as a static one-time event driven by top-down antecedents (e.g., TMT attributes and behaviors, organizational structures). Yet, strategic consensus is increasingly conceptualized as a dynamic emergent phenomenon that arises through networked interaction processes connecting managers across organizational levels. The limitations of prior research are understandable given the difficulty involved in conducting research on the antecedents of strategic consensus. For example, gaining access to a sufficient sample of organizational leaders can be prohibitive. As a result, much of the theorizing about strategic consensus is based on cross-sectional, survey research.

However, there are likely to be bi-directional, recursive, and otherwise complex relationships between antecedents and outcomes of strategic consensus that were outside the scope of prior research. Indeed, there is a noticeable lack of dynamic, multi-level theory explicating the consensus process at the individual, group, and organizational level as a result of the lack of requisite data and methodology (Wooldridge et al., 2008). Moreover, static approaches to studying strategic consensus limit our ability to understand what actually fosters the development of strategic consensus. That is, cross-sectional input-output research may identify potentially relevant relationships and expand the nomological network of consensus, but does not clarify *how* and *why* consensus emerges (Raes et al., 2011). Thus, the process of strategic consensus formation is currently a “black box” that is poorly understood.

I suggest that multilevel and complexity theories provide important insight into the process of strategic consensus through the lens of emergence (Holland, 1992; Klein & Kozlowski, 2000). Many emergent team-, system-, and organizational-level phenomena are rooted in the affect, cognition, and behavior of individuals and the interaction processes among them (Vallacher et al., 2015). For example, in cooperative settings, communication is the vehicle through which information is transferred from one individual to another. Within dyadic interactions among group members, receiving information results in affective, behavioral, or cognitive responses from the recipient. This response — either directly or indirectly— provides information to others, and results in a cognitive, affective, or behavioral response of their own (i.e., autocatalysis; Contractor & Siebold, 1993). Through this cycle of action and reaction, characteristics of individuals either coalesce or diverge creating a higher-order phenomenon such as a collective cognitive state (i.e., consensus; Morgeson & Hofmann, 1999). From this perspective, the elements that comprise strategic consensus originate at the individual level with managers' perceptions of strategic priorities and develop through dyadic processes of interaction among managers across organizational levels. That is, each employee's perceptions regarding strategic priorities is shaped by whom they interact with and additionally, whom they allow to influence their perceptions (Joseph & Gaba, 2020; Rapert, 2002)

CHAPTER 3

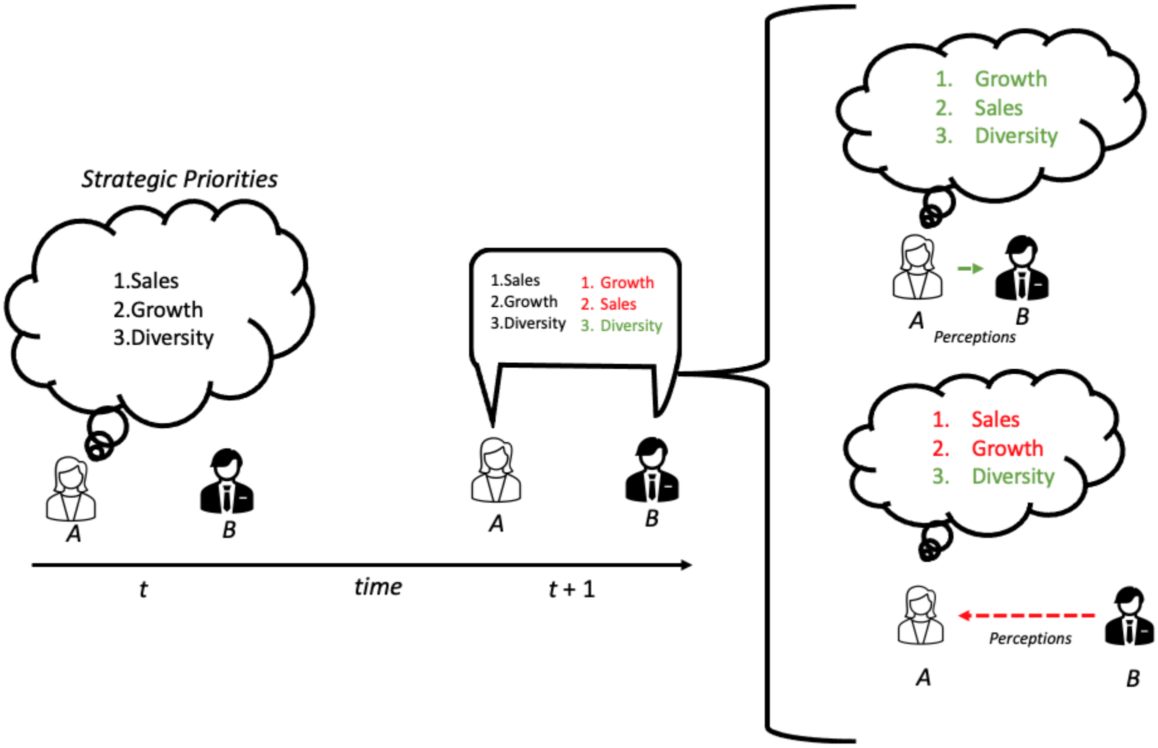
THEORETICAL MECHANISMS OF STRATEGIC CONSENSUS EMERGENCE

Drawing from micro-level research investigating the emergence of shared mental models within small teams (e.g., Grand et al., 2016; McComb, 2007), I conceptualize the emergence of strategic consensus across managerial levels using a dynamic process-oriented approach. Specifically, I argue that perceptions regarding strategic priorities develop and change *within* the minds of managers through *dyadic* interaction processes among the managers as well as through *individual* learning and decision-making processes that can occur during or after each dyadic interaction. Figure 3.1 picture below illustrates the basic dyadic building blocks of strategic consensus emergence. At Time *t*, Actor A holds an initial perception about the ranking of the strategic priorities of their organization (e.g., sales, growth, diversity). Actor A then *chooses* to participate in an interaction with Actor B where strategic priorities are discussed. During that interaction, Actor A has the opportunity to learn about or *consider* Actor B's perceptions of the organizations' strategic priorities (and vice versa). Moreover, Actors A or B might even *change* their perceptions of strategic priorities during the interaction and/or they may change their perceptions of one another (e.g., their willingness to interact again in the future). This process -- where managers *select* interaction partners, *consider* those partners' perspectives (or not), and potentially, *change* their own perspectives -- forms the foundation of strategic consensus emergence.

Figure 3.1

The Micro-level Processes Driving Strategic Consensus

Note: Actor A begins with their own strategic priorities in rank order at t = 0. At (t +1), Actor A chooses to interact with Actor B. During the interaction, information regarding strategic priorities is transmitted. Actor A may then act upon that information by either updating their priorities or keeping their priorities the same. Actor A's decision is based upon their perceptions of Actor B. Actor A may also update these perceptions based on the nature of their interaction.



Of course, *numerous* dyadic interactions are likely to happen simultaneously and over time among many upper- and/or middle-level managers within an organization. Thus, I argue that strategic consensus arises through dynamic *networked* processes of communication and influence linking members of upper- and middle-level management. For simplicity, in the remainder of this dissertation, I refer to the networked set of upper- and middle-level managers who are involved in strategy development and implementation as the **‘*strategic leadership***

***system*' (SLS).** Prior research on emergence, including research on emergent phenomena in organizations, has demonstrated that fundamental 'rules', 'principles', or 'tendencies' at micro-levels of analysis can give rise to macro-level patterns (Fulmer & Ostroff, 2016; Grand et al., 2016; Roberson & Williamson, 2012; Serban et al., 2015; Walter & Bruch, 2008). In this chapter, I leverage this approach to develop a series of postulates, and mathematical representations of those postulates, that articulate the tendencies guiding managers' *selection* of alters to discuss organizational strategy, their willingness to *consider* those alters' perspectives, and their willingness to *change* their strategic priority perspectives and/or their opinions of those alters during and following the interaction.

Tendencies Guiding the Selection of Alters

As illustrated in Figure 3.1, in the first phase of the dyadic interaction process, Actor A 'selects' another alter to communicate with about strategic priorities. Research on organizational communication networks offers extensive guidance regarding the fundamental principles guiding the process of alter selection for communication. For example, prior research suggests that trust is one of the primary determinants of knowledge exchange within organizations. As such, considerable research has investigated the foundations of trust in relationships (Gupta, Ho, Pollack, & Lai, 2004; Jazaieri, Logli, Campos, Young, & Keltner, 2019; Levin & Cross, 2004; Renzl, 2008). From this research, factors such as task interdependencies, interaction history, and individual differences have been found to be foundational to the communication process (Costa & Fullmer, 2018; De Jong, Dirks, & Gillespie, 2016; Williams, 2016).

Generally, individuals communicate with those they have communicated with in the past. Scholarship has taken one of three perspectives to explain such relational consistency which are 1) relational inertia, 2) rational approaches, and 3) uncertainty reduction approaches. First, evolutionary theories of communication and relational inertia propose that, ceteris paribus, individuals prefer to leverage existing communication relationships (Contractor et al., 2006; Hannan & Freeman, 1984; Kim et al., 2006). Evolutionary theory and relational inertia proffer several justifications for this preference. First, existing relationships are associated with greater trust because of repeated interaction. Through repeated interaction, individuals are given the opportunity to demonstrate reliable behavior and that they can be trusted. Second, individuals adapt over time to align with their relationships by changing their behaviors and cognitions in accordance with the information that they receive. This may result in becoming entrenched in a particular area, changing taskwork, or using personalized forms of communication. Third, existing relationships form the basis of identity, and therefore possess information regarding shared values and beliefs. Each of these factors results in highly valued relationships that serve as a disincentive for seeking out new sources of information (Festinger,1954; McPherson et al., 2001).

Second, game-theoretic or rational theories argue that individuals form and dissolve communication relationships based on perceived cost versus benefit, choosing to retain ties that are costly to develop, and those that are associated with increased value (Wever, Martens, & Vandenbempt, 2005). Finally, from a less rational perspective, theories of uncertainty reduction and cognitive dissonance suggest that forming new relationships is a source of discomfort. Specifically, forming new relationships comes with increased uncertainty due to a lack of knowledge about the new interaction partner, and may expose individuals to information that does not conform with their knowledge and/or beliefs (Cartwright & Harary; 1956; Festinger,1954; Lewicki, McAllister, & Bies, 1998).

One way that individuals develop trust through interaction is through taskwork, making *task interdependence* a primary determinant of trust and subsequent exchange of knowledge within organizations. Task interdependence reflects an individual's interpretation of the relationship between tasks and the coordinative behaviors that are enacted as a result (Wageman, 1995). A consequence of task interdependence is that workflows often dictate that specific individuals interact more or less frequently than others, fundamentally influencing their affect, behavior, and cognition in relation to one another. For example, task interdependencies may require that individuals coordinate their actions, and leverage each other's knowledge and or skills to be successful (Hollingshead, 2001; Olabisi & Lewis, 2018; Rico et al., 2018). Further, scholarship on intergroup dynamics suggests that interdependence can foster superordinate identification. In other words, due to the frequency of interaction, individuals who would have normally seen themselves as members of distinct organizational units or social groups, begin to cohere under a task-related identity (Contractor et al., 2006; Yuan, et al., 2010).

Postulate 1: SLS member *i* is more likely to communicate with *j* if *i* and *j* have communicated in the recent past.

Postulate 2: SLS member *i* is more likely to communicate with *j* if *i* and *j* share a tie in the organizational workflow network.

At a more granular level, individuals must also decide *between* existing contacts when choosing who to communicate with. When doing so, individuals rely upon the magnitude of trust in their existing relationships. The preference for choosing those who are the most trusted is explained by the fact that trust reflects confidence in the actions of another in uncertain circumstances. In the context of collaborative and coordinative action, the ability to rely upon others is critical. Indeed, in group environments where people must work together on complex tasks, distinct knowledge, skills, and abilities must be pooled together to accomplish objectives (Olabisi & Lewis, 2018; Mathieu et al., 2001). As a consequence, individuals must rely upon others for their unique contributions and trust that they will behave according to expectations. Doing so requires taking on risk and uncertainty. In the case of collective task performance, trust is an important tool that can be used to avoid uncertainty. Those who are trusted are seen as having a sense of credibility, or that they are a source of expertise and that they can be expected to communicate appropriate information (Giffin, 1967). For example, when someone is viewed as competent, able to carry out their actions, and considerate of the needs of others, their behavior is viewed as more predictable (Colquitt et al., 2012).

Postulate 3: SLS member *i* is more likely to communicate with *j* when *i's* level trust in *j* is higher.

Given that trust influences whom communicates with whom, it is important to understand how some individuals gain more trust than others. Sociology research and work on group dynamics tells us that in collaborative task environments individuals use identity as a primary source of trust information. Indeed, there is a well-established body of evidence highlighting the importance of group identification (Greco et al., 2022; Hogg, 2000; Tajfel, 1974). Group identification serves many important purposes. For example, self-categorization theory proposes that individuals place themselves and others into categories based on their salient characteristics as a heuristic for processing their social world. Social identity theory further explains how these social categories influence a person's thoughts, behaviors, and feelings. Specifically, individuals use their identification with a group as a source of self-esteem. To protect their self-esteem, differences between their group and other groups are emphasized while the characteristics of group members are given greater importance. Given the significance of group memberships for the self-concept, it is easier to place trust in group members because it is unlikely that a group member would betray trust. Similarly, groups often have associated archetypes and norms. Consequently, it is easier to predict the behavior of group members, further fostering trust.

Postulate 4: SLS member *i* is more likely to trust *j* if *j* is a fellow teammate rather than a member of another team.

The second way that individuals determine who to give preference to is through the social influence — or power — of their potential interaction partners. According to trust scholars, the foundations of cognitive trust are perceptions of ability, benevolence, and integrity (Giffin, 1967). Through schemas and expectations, the characteristics of ability, benevolence, and integrity become associated with specific organizational roles. For instance, leaders are evaluated as high on ability and credibility due to their position, as leaders are believed to have achieved their role, in part, through being highly skilled in their area of expertise (Borgatti & Cross, 2003). Indeed, formal leaders derive power from their expertise by demonstrating competence, ability, and skill through communication (French et al., 1959; Langlinais, 2022). Power gained from expertise means that individuals pay more attention to their views and are more likely to adjust their cognitions to be more congruent with those who wield power (Cartwright & Harary, 1956; Cialdini & Goldstein, 2004; Heider, 1946). Research on status beliefs further states that perceptions of status are related to certain individual differences. By relating certain characteristics such as organizational role or age with status, individuals develop and rationalize perceptions of their social environment. For example, the association between leadership and competence justifies the fact that leaders are sought out, granted more trust, and given more resources (Ridgeway & Erickson, 2000).

Postulate 5: *SLS member i is more likely to trust j if j occupies a higher (rather than lower) formal position of authority.*

Despite the natural preference to communicate with existing contacts, there are still instances when new relationships must be formed. Sociology research tells us that, when forming new relationships, individuals leverage information from their social environment to determine who to communicate with. For example, when deciding to interact with someone new it may be difficult to make an informed decision about who can be trusted and prove to provide beneficial information. One way that individuals may gather information to make such decisions is through people that they currently interact with. For example, properties of commonly observed social structures such as small worlds demonstrate that mutual acquaintances tend to already know each other better than complete strangers (Watts & Strogatz, 1998). The ability to infer the characteristics of a mutual acquaintance is particularly helpful when identifying new connections. The idea of connecting with "friends of friends" originates from theories of balance and triadic closure, which propose that people seek congruence in their relationships (Cartwright & Harary, 1956). In the case of a positive relationship — where two people think positively of each other — the motivation to create balance would encourage someone to form yet another positive relationship with a mutual acquaintance to form a triad (Pham et al., 2021). Having a common partner also provides legitimacy to the new potential contact and makes it more likely to form a tie (Gulati & Gargiulo, 1999).

Postulate 6: *SLS member i is more likely to communicate with j if i and j are both connected to a third SLS member k.*

When considering how strategic communication takes place, an important consideration is also the degree to which individuals choose to engage in strategic conversations. For example, due to perceived role responsibilities, individual differences, or incentives, some people may be more active in strategic conversations than others. Indeed, research suggests that individuals aim to fulfill the expectations of their social roles, such as leaders being more active in communication (Ridgeway & Erickson, 2000; Rogers, 2015; Rogers & Smith-Lovin, 2019). The consequences of communicative activity are a key question in sociological research. Sociological scholarship suggests that central individuals are positioned in what is referred to as structural holes, or locations in the network whereby they form a bridge between otherwise disconnected clusters. Such a position places the individual in the role of an informational broker who controls the flow of information throughout the network (Burt, 2004). The role of broker is further associated with increased activity. For instance, activity theory states that the likelihood of an individual engaging in a relationship with an alter is a function of the number of indegrees that they have (i.e., popularity; Yap & Harrigan, 2014). The relationship between indegree and outdgree in networks reflects a fundamental property of networks which is that those who are already more connected may also tend to connect more with others (i.e., the Matthew effect or preferential attachment; Barabasi & Albert, 1999; Merton, 1968). This can be explained by the fact that high-indegree centrality is a position of advantage. Thus, not only are central individuals highly informed, but are also optimally positioned to communicate information to all other members of the network, making them more likely to communicate with others (Reinholt & Foss, 2011; Burt, 2004; Ahuja et al., 2003).

Postulate 7*: SLS members vary in their communication activity levels such that some SLS members make more attempts to communicate about strategic priorities more broadly (with more alters) than other members.*

Tendencies Guiding the Consideration of Alters' Strategic Priorities

After selecting someone to have a strategic conversation with, the decision must be made as to whether to change perceptions of strategic priorities. This decision may come before strategic communication even takes place as a result of an immediate realization of extreme differences, or may occur after a conversation while weighing what information was exchanged. The most important decisions that must be made are whether any information is relevant, if the source can be trusted, and the new information is related to their current schema of organizational strategy. Referring back to Figure 3.1, Actor A has chosen to interact with alter B. During their conversation, strategic information is exchanged. Now, Actor A must decide whether to update their priorities based off of that conversation after considering their relationship, the individual characteristics of alter B, and how the information received relates to their current priorities.

Much like the decision of who to communicate with, the decision of whether to consider the priorities of others is also a function of interpersonal trust. Trust is based on similarity in beliefs because those with similar beliefs think in similar ways, making their behaviors more predictable and associated with less risk (Nowak et al., 2019). Moreover, those who share our beliefs are also easier to communicate with, making communication more efficient and effective. Specifically, when people have a shared concept of a topic (i.e., a shared mental model) there is less risk of misinterpretations and less effort expended communicating (Klimoski & Mohammed, 1994; Korsgaard et al., 2008). Further, theories of selective exposure propose that people seek out views that support their own and avoid those that are contradictory (Flache et al., 2017; Hart et al., 2009; Li & Porter, 2022). Individuals also tend to seek out others with similar opinions due to value homophily, as well as cognitive dissonance and balance. The overarching idea driving all three of these theoretical perspectives is that individuals are motivated to avoid and/or reduce feelings of conflicting cognitions (Cartwright & Harary 1956; Festinger, 1954; Ertug et al., 2022; Kan et al., 2021; McPherson et al., 2021; Stroud et al., 2014).

Postulate 8: *During an interaction, an SLS member will only* <u>*consider*</u> *an alter's strategic priorities if the alter's strategic priorities are sufficiently similar to the SLS member's strategic priorities.*

Individuals also differ in their willingness to listen or allow themselves to be influenced by others. This phenomenon can primarily be explained by research on attitude strength. Scholars suggest that individuals vary in the conviction through which they adhere to their attitudes. There are several explanatory mechanisms for the strength to which attitudes are held including social identity, social network composition, and social power (Eaton, Majka & Visser, 2008). Social power refers to the ability for someone to control the resources and or outcomes afforded to others (French & Raven, 1959). Importantly, social power has a strong relationship with resistance to influence and attitude strength (Eaton et al., 2008). Moreover, the strength to which attitudes are held fundamentally impacts an individual's ability and/or willingness to process new information. For instance, when individuals hold strong attitudes they pay less attention to attitude-relevant information and may instead rely upon heuristic methods of processing new information. Theories of affective states also suggest that individuals adhere to the expectations associated with their roles. For example, leaders may be less open to new ideas, whereas subordinates may behave more submissively (Briñol, Petty, Valle, Rucker, & Becerra, 2007). Importantly, as suggested by definitions of power, social influence is not constrained only to formal leadership. Indeed, research on informal leadership has provided continued evidence that leadership can occur outside of formal organizational structures. Indeed, theories of functional leadership propose that leadership is a behavior that is enacted, and not simply a formal role (Carter et al., 2020). Specifically, the behavior of leadership entails removing obstacles and providing necessary resources for goal accomplishment (Morgeson, DeRue, & Karam, 2010). From this perspective, those that engage in these behaviors may be seen as more influential in terms of their ability to enact change. As a result, individuals are more likely to listen to their opinions given their role, as well as the perceived competence and experience afforded by it.

Postulate 9: *SLS members who occupy higher positions of authority in the organization are less likely than SLS members who occupy lower positions of authority to consider the strategic priorities of an alter who holds priorities that differ from their own.*

Postulate 10: *SLS members are more likely to consider the strategic priorities of more 'influential' alters than they are to consider the strategic priorities of less 'influential' alters.*

Tendencies Guiding the Willingness to Change Strategic Priority Perceptions

The next step in the process of the strategic conversation is updating perceptions of strategic priorities. It is important to note the difference between determining whether to consider the priorities of someone else and determining how much to update priorities. In the previous step, the actor is using initial information to determine whether a conversation is worth seeing through, or if effort should even be put into considering the opinions of the alter. At this stage however, the determination is regarding the degree of change (if any) that will occur and implementing that change. As can be seen in Figure 3.1, Actor A has now evaluated the information provided through the conversation. Actor A now takes into consideration their own strategic priorities, those of the alter, their differences, and the characteristics of alter B.

A key factor in the determination of whether to change an opinion is the degree to which the new information aligns with current beliefs. One way that this alignment is evaluated is by the degree of similarity or difference. The idea of evaluating differences of opinions comes from Social Judgment Theory, which proposes that people have three different intervals that surround their attitudes. First, there is an interval of acceptance whereby new information is integrated into current perceptions. Second, there is an interval of noncommitment where the individual has no interpretation of the new information. Finally, there is an interval of rejection where new information is seen as too discrepant (Granberg & Sarup, 1992). The way information is incorporated into current perceptions depends upon where it falls within that individual's different categories. When information lies within the interval of acceptance, the individual chooses to integrate that information into their perception. However, information evaluated to be in any of the other intervals is ignored (Stefanelli & Seidl, 2017). The reason for this process is because of confirmation bias and cognitive dissonance. Both theories of confirmation bias and cognitive dissonance propose that discordant information creates feelings of uncertainty which are preferably avoided. As such, people choose to seek out information that supports their own beliefs (Festinger, 1954; Nickerson, 1998). Too reduce uncertainty people attempt to make sense of their environment (i.e., sensemaking). When information from others confirms a particular interpretation of the environment, uncertainty is reduced.

Postulate 11: *After considering an alter's perspective, SLS members will change their own strategic priorities to become more similar to the alters if the alter's strategic priorities are sufficiently similar to the SLS members' previous strategic priorities.*

Individuals may also differ, however, in the degree to which they believe in their strategic priorities, or their willingness to listen to the opinions of others. For example, research on attitude strength refers to resistance to change as a defense mechanism (Eagly & Chaiken, 1995; Howe & Krosnick, 2017). Scholars have found that an attitude's importance may be determined by such factors as its relationship with social identity, as well as its relevance to expertise or its personal relevance. Indeed, expertise is related to a reduced willingness to integrate new information from others, and alternatively, individuals are more willing to integrate information from those who have a strong belief or high confidence in their opinion (Cho, 2018; Nowak et al., 2019).

Expectation states theory (EST) further proposes that hierarchies of influence arise because of task expectations. Expectations are formed because of resource distributions, individual characteristics, and patterns of interaction. The role expectations inform individuals about the status of others and their subsequent behaviors towards them (Correll & Ridgeway, 2006). For example, individuals in positions of power who are popular or who have access to significant resources are seen as being more important for task accomplishment and therefore of greater value. Because their contributions are seen as more valuable, they are granted more influence. Furthermore, social impact theory proposes that the degree to which an individual is influenced by others is a function of the strength, immediacy, and number of sources of information. Of particular importance is strength, which is determined by the "status, salience, power, importance, or intensity of a given source to the target" (Latane, 1981, p. 344). Thus, individuals in positions of authority can make others more willing to change their opinions, while those with less authority or influence are less able to do so.

From a sociocognitive perspective, formal authority within an organization also impacts the methods through which information is processed. For instance, the elaboration likelihood model proposes that there are superficial as well as in depth methods of information processing, and that individuals decide between the two processes based on available information. The determination to use either deliberative or heuristic processing is determined by one's degree of expertise, ability, or resources to process the information in depth. The circumstances surrounding different members of organizations may in fact facilitate and/or hinder different forms of processing. Leaders have expertise in strategy, making them more likely to process strategic information using elaborative methods (Cacioppo & Petty, 1984; Petty & Briñol, 2011). A consequence of formal social power is also that leaders are expected to be resolute, resistant, and to strongly hold opinions. Importantly, because they are expected to be more zealous, individuals in positions of power behave in ways that fulfill these expectations (Eaton et al., 2008).

Postulate 12: *SLS members who occupy higher positions of authority in the organization are less likely than SLS members who occupy lower positions of authority in the organization to change their strategic priorities.*

Postulate 13: *SLS members are more likely to change the strategic priorities of alters that are more susceptible to influence than they are to change the strategic priorities of alters that are less susceptible to influence.*

Tendencies Guiding the (Updated) Selection of Alters

In the final stage, the results of the interaction are used to update SLS members' perceptions about the person they communicated with. Referring to Figure 3.1, actor A may engage in two possible behaviors. First, they may have integrated the information provided by alter B, and therefore increase positive attitudes towards that person. Second, they may alternatively refuse to integrate the information and leave the relationship as it is.

As a result of strategic conversations, individuals change their perceptions of the trustworthiness of their communication partner to reflect an updated belief in whether that person provides useful information, that information is relevant to their opinions, and their perceptions of them on other characteristics. This updating reflects the individual determining their willingness to seek out this person again in the future. Generally, more trust is placed in those with similar opinions and less in those who hold dissimilar viewpoints (Nowak et al., 2019). In fact, scholarship on attitude change suggests that the degree to which trust is placed or withdrawn is proportional to the difference of opinions (Lord et al., 1979). Specifically, according to theories of biased assimilation and social judgment, for opinions that are within an individual's interval of acceptance, the smaller the discrepancy, the more trust is placed in that relationship. On the other hand, for opinions in the interval of rejection, the greater the discrepancy, the more trust is withdrawn from the relationship (Lord & Taylor, 2009; Turner & Smaldino, 2018). Moreover, evolutionary theory of communication suggests that individuals place more trust in people they previously interacted with who are like themselves. This is because they can communicate efficiently because of shared characteristics, like values, goals, and cognition.

However, people also seek to avoid differing opinions that conflict with their own, causing cognitive dissonance. To reduce dissonance, people may try to avoid situations or beliefs that contradict their own (Festinger, 1954). As such, after an interaction, people can adapt their perceptions of trust in a specific interaction partner because of receiving information that conflicts with their perceptions, and this reaction is proportional to the difference between their perceptions (Festinger, 1954; Groeber et al., 2014).

Postulate 14: *SLS members update their trust in an alter based on the similarity of their strategic priorities after an interaction.*

CHAPTER 4

MODEL FORMALIZATION AND AGENT-BASED MODEL DEVELOPMENT

Having specified a verbal theory of strategic consensus emergence, the next step was to formalize this model mathematically so that computer algorithms could be developed representing the verbal theory. To create the formal specification, I began with a pre-established class of models from the sociophysical literature on continuous opinion dynamics called bounded confidence models. Using the bounded-confidence model allowed for me to start from where past validated models left off, reducing the burden of model development, providing additional support for model validity, and relating the final model to similar scholarship. With the bounded-confidence model as a foundation, I incorporated additional formal specifications to match my verbal theory. The final formal model was then translated into an agent-based model by converting formal mathematical specifications into computer code using the NetLogo programming language (Wilensky, 2023). In this chapter I further describe how I formalized the verbal and mathematical theory described in Chapter 3 as a dynamic network model. I first detail aspects of established sociophysical models of consensus formation called bounded confidence models that were used as a foundation for my model. Then I describe the additional formal theory that was added to the bounded confidence model to match my verbal theory. Finally, I explain the algorithmic interpretation of the formal model through the procedural rules that drive the final computational model.

The dynamics surrounding opinion formation are commonly studied in fields such as statistical physics and mathematics, where closed-form models are used to examine the characteristics of individual entities and how their interactions lead to different collective outcomes. Given the rich history surrounding opinion dynamics research, there are several different established classes of models, each with different characteristics that coincide with different theoretical perspectives (Grabisch & Rusinowska, 2020). A particular form called the bounded confidence model was adopted to create the computational model due to its alignment with my theoretical assumptions.

Bounded Confidence Models

Bounded confidence models describe models of opinion dynamics where agents have a tolerance that determines if they are willing to change their opinion. Traditionally, the bounded confidence model places a uniform interval around the agent’s opinion, to act as the agent's interval of acceptance. In the continuous form, each agent's opinion is represented as a number within the open unit interval (0, 1). The bounded confidence model also incorporates the idea that if two actors are sufficiently far apart from each other in terms of their opinions then they will not change their opinion (Flache et al., 2017).

Deffuant-Weisbuch model. The Deffuant-Weisbuch model (sometimes referred to as the Deffuant model) also represents opinions as a number within the open unit interval (0, 1) (Deffuant et al., 2000). Traditionally in this model, during each iteration only one agent is chosen to interact and they must randomly select one other person as their partner. Should the selected partner be within the confidence bound then both actors in the interaction adjust their opinion. Traditionally, the relationship is assumed to be reciprocal such that $(x_i \rightarrow x_j)$ $(x_j \rightarrow x_j)$. A learning parameter μ controls how fast an individual is willing to change their opinion. As $\mu \rightarrow$

1, their opinion changes to that of their interaction partner after each round. As $\mu \rightarrow 0$ they do not change their opinion during interactions.

To reflect the specified verbal theory, several modifications were made to the traditional Deffuant model. First, the original Deffuant model assumes homogeneous tolerances (confidence bounds), or that everyone is equally susceptible to influence. However, the present theory states that some individuals may be less/more susceptible to influence than others. Thus, the assumption of homogeneous confidence bounds was relaxed to give leaders and followers different confidence levels. The Deffuant model also assumes that all individuals have equal access to everyone else. To account for the fact that relationships are patterned, directional, and possess strength, a directed interaction network was imposed, whereby communication relationships are reflected by directional ties, and individuals are only able to interact with those that they are connected to. Additionally, the network used in the present model was made adaptive, allowing for tie severance and creation, tie decay and strengthening, and changing node states.

The Formal Model

The formalized version of each postulate from the verbal theory is presented in Table 4.1. Each formal operationalization for the verbal postulates, along with formalizations required to establish the initial conditions is explained in further detail below.

Table 4.1

Summary of Verbal and Formal Model

Theoretical Postulates	**Formal Operationalization**
Tendencies Guiding the Selection of Alters	
Postulate 1: SLS member *i* is more likely to communicate with *j* if *i* and *j* have communicated in the recent past.	$P_c = U(0,1)\begin{cases} > .99, j \notin N_i \\ < .99, j \in N_i \end{cases}$
Postulate 2: SLS member *i* is more likely to communicate with *j* if *i* and *j* share a tie in the organizational workflow network.	$P(y_{ij(c)}\ \ ) = P(y_{ij(c)} \mid\ y_{ij(w)})$
Postulate 3: SLS member *i* is more likely to communicate with *j* when *i's* level trust in *j* is higher.	$P_c\ \alpha\ t_{ij}$
Postulate 4: SLS member *i* is more likely to trust *j* if *j* is a fellow teammate rather than a member of another team.	$t_{ij} = M_j \cdot M_p, where\ M_j = \begin{cases} team_i = team_j, 1 \\ team_i \neq team_j, 0 \end{cases}$
Postulate 5: SLS member *i* is more likely to trust *j* if *j* occupies a higher (rather than lower) formal position of authority.	$t = TL_j \cdot TL_p + CEO_j \cdot CEO_p,$ $where$ $TL_j = \begin{cases} TL = 1, 1 \\ TL \neq 1, 0 \end{cases}$ $CEO_j = \begin{cases} CEO = 1, 1 \\ CEO \neq 1, 0 \end{cases}$

Postulate 6: SLS member *i* is more likely to communicate with *j* if *i* and *j* are both connected to a third SLS member *k*.

$$P_c = \forall_j \in N \left\{ \begin{array}{l} = \emptyset, |\Gamma(i) \cap \Gamma(j)|, k \in_R S \\ \neq \emptyset, |\Gamma(i) \cap \Gamma(j)|, k \in_R N \end{array} \right.$$

Postulate 7: SLS members vary in their communication activity levels such that some SLS members make more attempts to communicate about strategic priorities more broadly (with more alters) than other members.

$$P_a \ \alpha \ influence_i$$

Tendencies Guiding the Consideration of Alters' Strategic Priority Perceptions

Postulate 8: During an interaction, an SLS member will only consider an alter's strategic priorities if the alter's strategic priorities are sufficiently similar to the SLS member's strategic priorities.

$$P_l = \left\{ \begin{array}{l} \sigma_{i(t)} - \sigma_{j(t)} < \mathrm{B}, 1 \\ \sigma_{i(t)} - \sigma_{j(t)} \geq B, 0 \end{array} \right.$$

Postulate 9: SLS members who occupy higher positions of authority in the organization are less likely than SLS members who occupy lower positions of authority to consider the strategic priorities of an alter who holds priorities that differ from their own.

$$B = \left\{ \begin{array}{l} ELT = 1, B_{ELT} \\ ELT = 0, B_{MM} \end{array} \right.$$

Postulate 10: SLS members are more likely to consider the strategic priorities of more 'influential' alters than they are to consider the

$$P_c = \frac{(B_i + influence_j) - min\,(B + influence)}{max(B + influence) - min(B + influence)}$$

strategic priorities of less ‘influential’ alters.	
Tendencies Guiding the Willingness to Change Strategic Priority Perceptions	
Postulate 11: After considering an alter’s perspective, SLS members will change their own strategic priorities to become more similar to the alters if the alter’s strategic priorities are sufficiently similar to the SLS members’ previous strategic priorities.	$\sigma_{i(t+1)} = \begin{cases} \sigma_{i(t)} - \sigma_{j(t)} < B, \sigma_{i(t+1)} = \sigma_{i(t)} + \mu(\sigma_{j(t)} - \sigma_{i(t)}), \\ \sigma_{i(t)} - \sigma_{j(t)} \geq B, \sigma_{i(t+1)} = \sigma_{i(t)}, \end{cases}$
Postulate 12: SLS members who occupy higher positions of authority in the organization are less likely than SLS members who occupy lower positions of authority in the organization to <u>change</u> their strategic priorities.	$\mu = \begin{cases} ELT = 1, \mu_{ELT} \\ ELT = 0, \mu_{MM} \end{cases}$
Postulate 13: SLS members are more likely to <u>change</u> the strategic priorities of alters that are more susceptible to influence than they are to change the strategic priorities of alters that are less susceptible to influence.	$\Delta = \mu + \left(influence_i - influence_j\right)$
Tendencies Guiding the (Updated) Selection of Alters	
Postulate 14: SLS members update their trust in an alter based on the similarity of their strategic priorities after an interaction.	$t_{ij(t+1)} = t_{ij(t)} + t_{ij(t)} \cdot (1 - t_{ij(t)}) \cdot (B - \vert \sigma_{i(t)} - \sigma_{j(t)} \vert)$

Model Initialization

Agent Attributes. The model is initialized by first creating *t* teams of size *n*, where *t* reflects the number of teams, and *n* represents the team size. The teams consist of $(n-1)$ middle managers and 1 team leader who is simultaneously a member of the TMT. The TMT consists of the leader of each functional team and the CEO who is only a member of the TMT and functions as its leader. The opinions of each agent are then initialized as a random number from the open unit interval (0, 1) selected from a normal distribution reflecting the tendency for individuals to have moderate opinions, and for extreme opinions to occur with low frequency. Each agent is also assigned a confidence bound reflecting their willingness to accept influence. Leaders and followers are assigned distinct confidence bounds — or tolerances — that can take on the value of any number within the open unit interval (0, 1).

A learning rate is also assigned to each agent, and this rate differs based on role. The learning rate represents the amount someone is willing to shift their perspective as a result of new information. Preference to rely on trust is also assigned to each agent as a homophily parameter. As the homophily parameter approaches 0, the outgoing strategic communication neighbor with the greatest trust is selected as the interaction partner for the current round with probability 1. As the homophily parameter approaches 1, all outgoing strategic communication neighbors are equally likely to be interacted with regardless of the value of trust. Middle managers and leaders get separate values for the homophily parameter reflecting that leaders have different preferences for interactions based on trust. The homophily parameter can take on any value within the open unit interval (0,1).

Network Attributes. Social networks are a way of visually representing and mathematically analyzing various forms of patterned relationships (Wasserman & Faust, 1994). At the most fundamental level social networks rely upon graphs consisting of nodes and edges[1]. Nodes may represent people, things, or events, while links represent the relationships that connect the different entities. Networks can possess several different features. First, links can be directed or undirected. In an undirected graph, every link from one node to another is assumed to be reciprocated (i. e., $i \rightarrow j \Rightarrow j \rightarrow i$). Alternatively, in directed networks, relationships are not assumed to be reciprocated (i. e., $i \rightarrow j \nRightarrow j \rightarrow i$). For instance, in a formal leadership network an employee may identify someone as their leader, but it is not presumed that the employee likewise leads them. Edges can also have weights which indicate the magnitude of the relationship between two nodes. Often these edge weights represent the frequency of interaction, or the strength of the relationship (Granovetter, 1973). Finally, nodes can also have characteristics that help explain some aspect of the network.

The present model consists of a network of directed strategic communication linkages[1], as shown in Figure 4.1.The initial within-team network structure is based on the work of Yamanoi and Sayama (2013) and is defined as

$$P_w(i) \sim (i/n)^w (i = 1, 2, ..., n)$$

Where $P_w(i)$ is the probability of an individual being initially selected as a strategic communication partner. *i* represents the agent id number, *n* is the size of the team, and *w* is the within-team network parameter. At low values of *w*, the initial number of within-team ties are evenly distributed throughout the team. At high values of *w*, ties are more likely to be formed

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[1] In the social networks literature relationships may be referred to as ties, links, or edges. Similarly, individuals may be referred to as nodes or actors. These terms are used interchangeably.

with those with higher id numbers (leaders), such that the network becomes increasingly centralized around the leader. In the current model, the possible values of *w* are 1, 3, 5, 10, 20, and 30. [2]The number of within-team ties is a separate parameter w_t that represents the within-team network density; or the number of ties that are present within the team out of the total possible number of ties on a directed network.

$$\frac{n}{n(n-1)}$$

Where n is the size of the team. The within-team network density ranges from (0, 1). It is important to note that as the within-team density increases, the relevance of *w* decreases. This is due to the fact that as networks become more dense the number of possible unique relationships decreases. For example, at a density of 1, all members of the network have directed connections with one another, and thus the ties cannot be structured. Next, the initial system communication network is established (Fig. 4.1). The system network is mathematically operationalized based on the equation by Yamanoi and Sayama, (2013), which describes system centralization as

$$P_b \sim c_i^b (i = 1, 2, ..., n)$$

Where *Pb is* the probability of an individual being selected as the origin or destination of a tie between teams. *i* represents an agent’s id number, *n* is the network size, *b* is the between-team network parameter, and *c* is the within-team degree centrality of each agent. The value of *b* can take on the values 0.1, 0.5, 1, 3, and 5. For lower levels of *b*, ties are randomly assigned throughout the system. For higher levels of *b*, ties originate from, and go to, team members with higher centralities. The number of between-team ties is specified through the b_t parameter that represents the density of the between-team network. The between-team strategic communication

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[2] While in some networks self-loops (connections to oneself) are theoretically relevant, they are excluded from the present study.

network density can take on values (0, 1). The number of possible between-team ties is calculated as

$$n_a(n_a - 1) - (Size_{teams}) * (Size_{teams} - 1)(n_{groups} - 1) + (n_{TMT})(n_{TMT} - 1)$$

Finally, each tie is assigned an edge-weight representing trust. This weight is a number from the open unit interval (0, 1) and is initialized as a random draw from a uniform distribution X ~ $\bigcup(0, 1)$. The trust weight is then modified after each interaction to reflect teammates, team leaders, and the CEO. For each relevant characteristic, the trust weight is adjusted by the relevant salience parameter which can take on any value from the open unit interval (0, 1).

$$Trust = CEO(CEO_{salience}) + Leader(Leader_{salience}) \\ + memberships(membership_{salience}) + \triangle\, trust$$

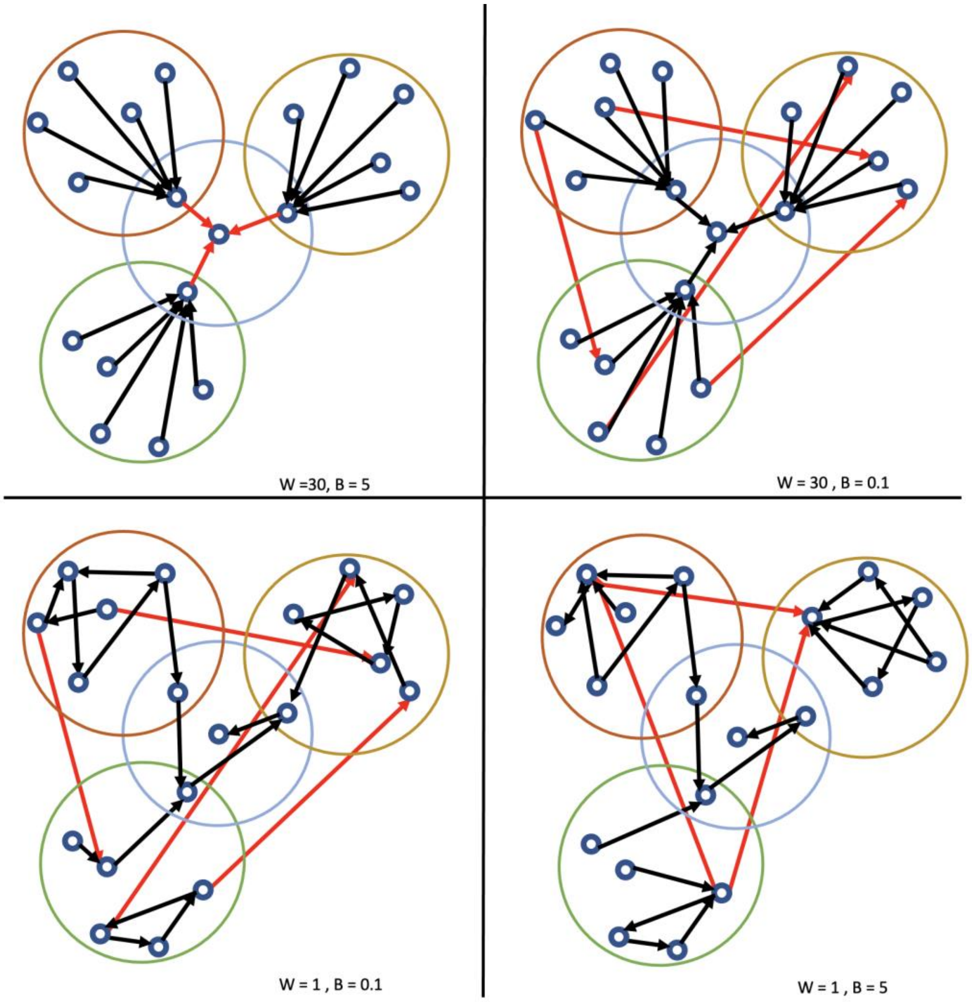
Processes. At each time step the following procedure is performed**:**

1. One agent in the model is chosen at random from a uniform distribution P_i ~ $\bigcup(0, 1)$.

2. With probability P ~ (1 - P_n) , the agent searches for one of its outgoing strategic communication link-neighbors to select as a strategic conversation partner. The neighbor is chosen with the probability of being selected based on the trust of the strategic-communication tie from the agent to the partner. The agent's trust preference is used as the temperature parameter in order to transform the link-weight into a probability through a softmax function (Sutton & Barto, 1998). Softmax functions are commonly used in reinforcement learning to indicate the probability of choosing between several actions based on the expected payoff of that action in comparison to the expected payoff for the composite of all possible actions.

Figure 4.1

SLS Centralization Characteristics



Note: Black ties are within-team, red ties are between-team. At high levels of W (A, B) ties are much more likely to go to leaders within each team, while at low levels (C, D) the ties are distributed at random. At high levels of B (A, D), ties start from, and go to, highly central actors regardless of formal position. At low levels of B (B, C), the ties are distributed at random.

At low levels of trust preference (τ) the individual with the highest trust (t_i) is selected with almost certainty ($P_j \sim 1$), while at high values all potential partners are equally likely to be selected $P_j \sim U(0, 1)$.

$$P_i = \frac{e^{(t_i/\tau)}}{\sum_{i=1}^{N} e^{(t_i/\tau)}}$$

3. With new-link-probability, instead of strategizing, the agent forms a new tie with another node in the network. The probability of any actor being selected is a function of how similar they are in strategy. The new-link-probability parameter can take on any value from the open unit interval (0, 1).

4. If two agents interact, the agent who is engaging the other agent in strategic conversation compares their strategy to that of their partner. Based on a heaviside equation, if the absolute value of the difference between the two strategies is less than or equal to their tolerance, then they update their strategy. The amount which they update their strategy to become more like their partners is dependent upon the learning parameter μ. If the absolute difference between the two strategies is greater than the tolerance B, then strategies are not updated.

$$o_{i(t+1)} = \begin{cases} o_{i(t+1)} = o_{i(t)} + \mu(o_{j(t)} - o_{i(t)}), & |(o_{j(t)} - o_{i(t)})| \leq B \\ o_{i(t+1)} = o_{i(t)}, & |(o_{j(t)} - o_{i(t)})| > B \end{cases}$$

$$o_{i(t+1)} = \begin{cases} o_{i(t+1)} = o_{i(t)} + \mu(o_{j(t)} - o_{i(t)}), & |(o_{j(t)} - o_{i(t)})| \leq B \\ o_{i(t+1)} = o_{i(t)}, & |(o_{j(t)} - o_{i(t)})| > B \end{cases}$$

Where $o_{i(t+1)}$ is the focal agent's strategy at $t + 1$, $o_{i(t)}$ is the focal agent's current strategy, $o_{j(t)}$ is the interaction partner's strategy, as the focal agent's tolerance.

5. The trust weight of the tie from the acting agent to the partner is updated according to the distance between their strategies and their tolerance for differing opinions. Thus, the closer their priorities are within the tolerance interval, the more trust is increased. However, outside of the interval, the further apart their priorities are the less trust remains.

$$t_{ij(t+1)} = t_{ij(t)} + t_{ij(t)} \cdot (1 - t_{ij(t)} \cdot (tolerance_i - |o_{i(t)} - o_{j(t)}|)$$

This represents a simplified version of Bayesian learning, where agents update their priori beliefs as a result of new information, subsequently updating the probability of that particular individual being selected as a partner in the future (Hayashi & Kryssanov, 2013).

6. If the agent does not have any outgoing strategic communication neighbors, then they form a new tie with another agent in the network, with preference given to those who share a tie with another alter.

Model Implementation

To develop the dynamic network model, the formal theory was translated into code in the NetLogo modeling language. Netlogo allows for functions to be specified that dictate the actions that an individual (i.e., agent) performs over time. The particular actions that are taken by agents in the model are specified in pseudocode (Figure 4.2), as well as in a flowchart (Figure 4.3) below.

Figure 4.2

Pseudocode for Agent-based Model of Strategic Consensus

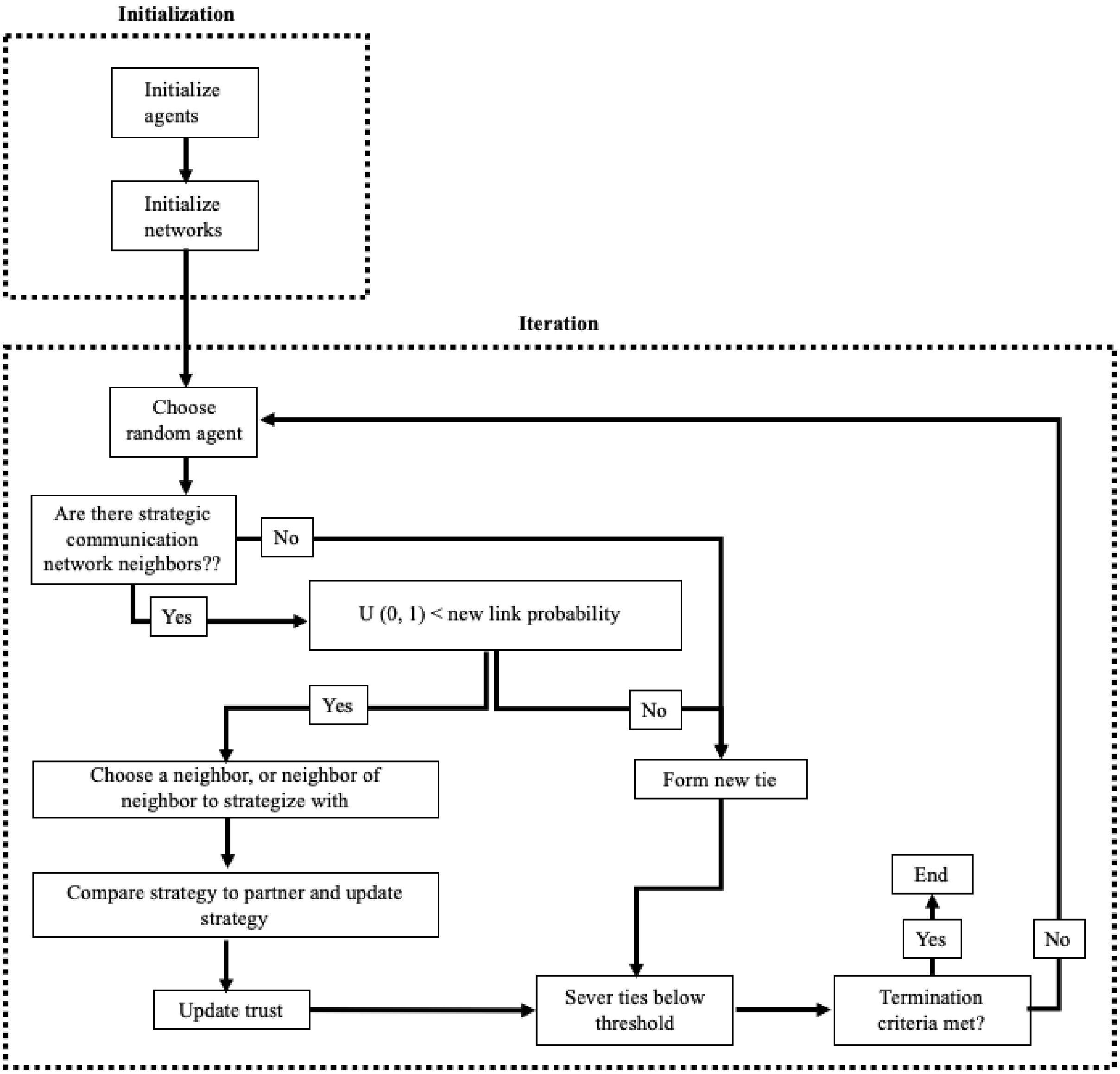
```
Initialize
   Set global variables and initialize all agents
   Create team membership, formal leadership, initial strategic communication, and strategic model ties based on parameters
   Assign agent attributes

Run

While (t <= $10^5$ or models != converged) do
   Select a weighted-random agent
      If (random-float 1 >= new-link-probability) do
         If (there are any strategic communication relationships) do
            Choose a communication partner in a weighted-random manner based on strength of trust and preference for trust
            Temporarily adjust tolerance based on partner's influence
            Compare strategic priorities
              If |si - sj| < tolerance do
                 Update strategic priorities to become more like partner based on learning rate and influence
                 Update trust
              End if
            Update trust based on strategic distance
         Else if (there are still people I am not communicating with) do
            If of the people I am not communicating with, there are individuals who are currently communicating with someone I am
               also communicating with do
               Randomly choose to communicate with one of the qualifying individuals
            Else
               Randomly choose to communicate with any agent
            End else
            End if
            Apply initial trust weight to the communication tie
      Else
         Else if (there are still people I am not communicating with) do
            If of the people I am not communicating with, there are individuals who are currently communicating with someone I
               am also communicating with do
               Randomly choose to communicate with one of the qualifying individuals
            Else
               Randomly choose to communicate with any agent
            End if else
         End else if
          Apply initial trust weight to the communication tie
   End
   If time since last interaction is greater than 0 do
      Decay trust
   And if trust is less than that which can be maintained do
      sever communication tie
   End
   For each possible pair of agents do
      Calculate strategic consensus
   End for
   Calculate all metrics
   If network has reached a stable state do
     END
      Else advance time 1
   End if
End while
Return measures
END
```

Figure 4.3

Flow Diagram of Computational Model



CHAPTER 5

ORGANIZATIONAL DATA TO REFINE AND VALIDATE MODEL

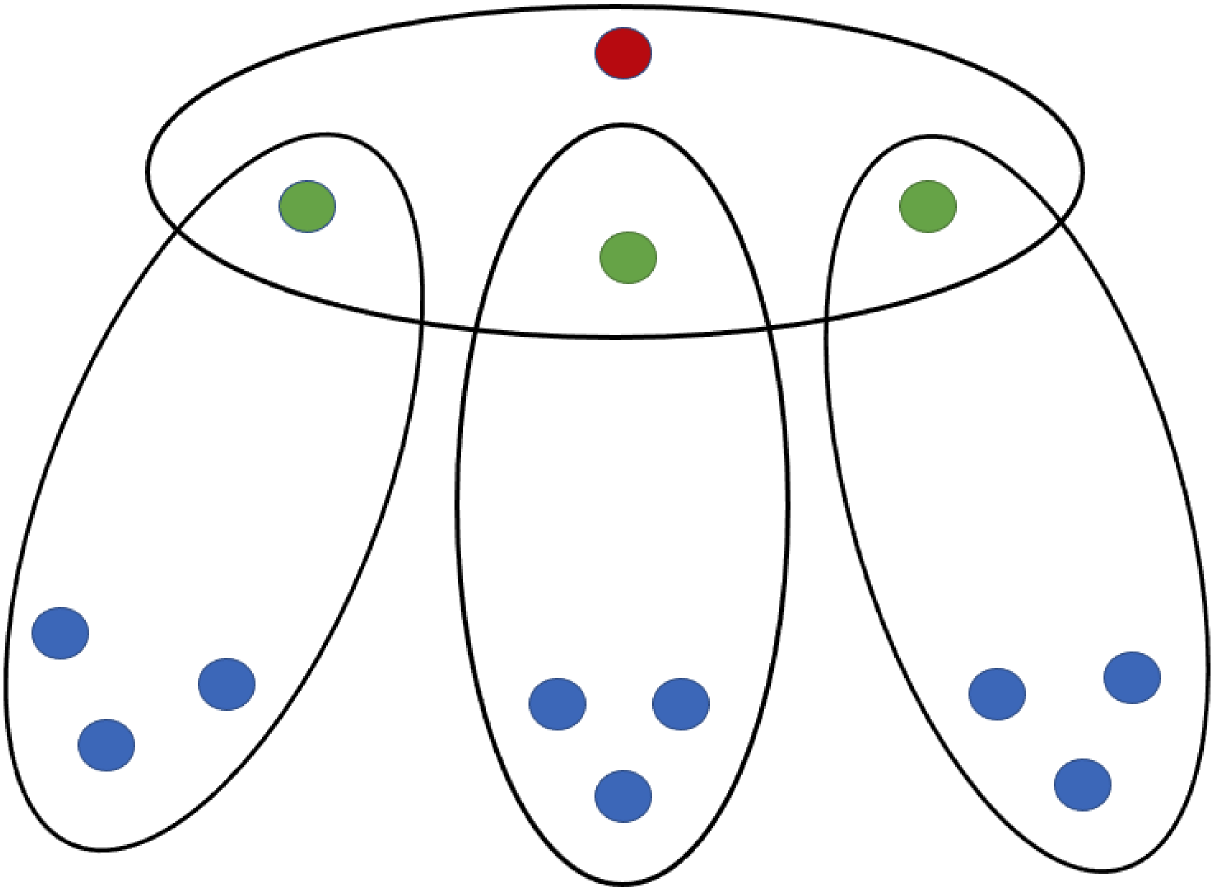
This chapter provides a detailed summary of the characteristics of the empirical data collected from top- and middle-level managers within four organizations that I used to parameterize and validate the agent-based model.

Participating Organizations

The data used to develop and test the agent-based model were collected from four organizations from different industries using a survey-based approach. The organizations were recruited to participate in the study and in exchange for their participation they were provided with a report of potential insights from the data collected. Participating organizations came from energy, higher-education, and healthcare industries. Overall, the organizations tended to have similar formal structures. The SLS structure of the organizations in the sample is shown in Figure 5.1. In the organizations a single CEO worked alongside TMT members who were also the leaders of their respective departments. Participating organizations were provided with surveys that assessed the structure and properties of the SLS within their organization. To participate in the survey individuals had to be considered part of the SLS. Detailed descriptions of each sample are provided in Table 5.1.

Figure 5.1

A Prototypical SLS Structure



Note: Departments are made up of middle managers (blue), and a leader, (green). Each leader is simultaneously a member of the TMT. The leader of the TMT is the CEO (red).

Table 5.1

Sample Description

Variable	Organization 1 (*n* = 85)	Organization 2 (*n* = 42)	Organization 3 (*n* = 53)	Organization 4 (*n* = 35)	
Age (SD)	49.7 (14.1)	44.2 (7.3)	43 (8.3)	44.6 (7.1)	44.23(9.29)
Gender	Women (52.9%) Men (47.1%)	Women (52.4%) Men (47.6%)	Women (32.1%) Men (67.9%)	Women (60%) Men (31.4) Non-binary (.09)	Women (58.13) Men (41.8)
Race	White (88.24%) Black (10.59%) Other (1.18%)	White (100%)	White (98.11%) N/A (1.89%)	White (100%)	White (100%)

Self-Report Survey Items Included in Analyses

Demographic characteristics (Table 5.1) were provided by the organizations prior to data collection. Table 5.2 provides a summary of all collected variables that were used to develop the model, and Table 5.3 provides descriptive statistics of relevant variables. Sociometric items were used to assess pertinent network structures. These items asked participants to identify those that they trust, deem as competent, and communicate with about strategy formulation and implementation. This data was used to calibrate model parameters and validate the results of virtual experimentation.

Strategic communication

Strategic communication networks were identified using a sociometric item assessing conversations with regards to the formulation of strategy. Broadly, the strategic process can be divided into two actions that co-occur; formulation and implementation. While both are relevant to the formation of strategic consensus, research suggests that consensus primarily forms during the formulation of strategy, as a strategy usually will not be implemented unless there is some degree of consensus within the TMT (Noble, 1999).

Strategic priorities

Each participant was provided with a list of strategic priorities that was developed with the aid of organizational stakeholders prior to the start of the study. Each participant was then asked to rank the strategies in order of priority, from most important to least important. To transform this information into a quantity representing the degree of strategic consensus, the Euclidean distance between the “Strategic vector” of each individual was calculated.

Table 5.2

Description of Model Variables Collected from SLS Survey Data

Variable	Type	Source	Description
Outcome variable			
Strategic priorities	Individual	Questionnaire	Strategic priorities were collected through the rank ordering method. Strategic priorities were identified prior to data collection through organizational SMEs. *Please rank the strategic goals of [your organization] (listed below) in terms of their importance to [your team]: (1 - most important; [n-goals] - least important).*
Predictor Variables			
Formal Role	Individual	Organizational Chart	Individuals were listed as either middle managers, team leaders, or the CEO. The CEO was reported as both the leader of the TMT and the CEO.
Team Membership	Individual	Organizational Chart	The functional team membership of each individual in the organization
Outgoing strategy formulation conversation ties	Network	Questionnaire	Roster style question, *With which of the following people do you regularly exchange information regarding formulating strategy? This information may address the competitive environment, the organization's current strengths or weaknesses, and how the organization can leverage its*

Variable	Type	Source	Description
			resources and capabilities to create competitive advantage
Team size	Contextual	Organizational Chart	Number of individuals within each functional team.
Number of teams	Contextual	Organizational chart	Number of functional teams within the organization.

Table 5.3

Descriptive Statistics of Collected Variables

	Organization 1		Organization 2		Organization 3		Organization 4				Overall	
							Time 1		Time 2			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Outcome variables												
Strategic Consensus	.93	.04	.62	.20	.63	.11	.59	.04	.60	.04	.67	.03
Group Strategic Consensus	.93	.02	.63	.20	.68	.10	.96	.04	.96	.04	.83	.16
TMT Strategic Consensus	.92	.03	.64	.24	.68	.10	.98	.03	.98	.02	.84	.17
Predictor Variables												
Outgoing Strategy Formulation Ties	17.23	9.73	21.96	11.67	11.46	6.79	11.58	7.91	8.33	6.21	14.11	5.43
Number of Groups	12	-	9	-	13	-	7	-	7	-	9.6	2.79
TMT Size	9	-	7	-	12	-	5	-	5	-	7.6	2.97
Group Size	5.75	4.27	5.3	1.57	5.08	2.9	5.83	3.76	7.67	6.83	5.93	1.02

Note: Means for network variables reflect network density.

This vector contained the rank for each participant on each strategy, in the order that the strategies were provided, such that the strategic rankings were in the same order across participants:

Participant 1: Ranking Strategy A = 2, Ranking strategy B = 1

Participant 2: Ranking strategy A = 1, Ranking strategy B = 2

The average was then taken of all agreement values across all participant dyads, resulting in a value that represents the average level of agreement. To calculate team-level strategic consensus, the Euclidean distance was calculated for each possible pair of team members, including the leader. The metric therefore represents the average level of agreement within each component group. The shared strategic priorities of the TMT were also partitioned out, due to the distinctive role of the TMT in the strategic process.

$$S_{C(D)} = AVG\left[\sum_{\{(a,b)\,|\,a \in A \wedge b \in B\}\; a \neq b} \left(1 - \frac{\sqrt{\sum_{i,j\,=\,1, i\,>\,j}^{n} \left(S_{c(a)} - S_{c(b)}\right)^2}}{\sqrt{n_s \cdot (n_s - 1)^2})}\right)\right]$$

$$S_{C(SLS)} = AVG\left[\sum_{\{(a,b)\,|\,a \in A \wedge b \in B\}\; a \neq b} S_{c(a)} - S_{c(b)}\right]$$

CHAPTER 6

MODEL EVALUATION

Critical to the success of any model is determining whether 1) the constructed model is a faithful representation of the verbal theory, and 2) that the results can be used for their intended purpose (i.e., validity; Thiele, 2015). This process is often referred to as verification, validation, and uncertainty quantification or VVUQ. The process used to test the current model follows current best practices for rigor in the modeling literature (i.e., Gelman et al., 2020; Rand & Rust, 2011; van der Vaart et al., 2015). The VVUQ framework was used to evaluate the proposed model. Following best practices, several tests were performed within each phase of the framework. The process used to examine the current model is listed in Table 6.1 below. In this chapter, I discuss the VVUQ process that was followed, the tests that were performed, and the results of those tests. In the first section, I discuss model *verification*, or how the code was examined for accuracy of implementation, through code reviews, testing of edge cases (i.e., simulating extreme values), and model docking (i.e., replicating findings from other models). The second section covers *validation* and describes the steps that were taken to demonstrate the relationship between the model and the system being studied on multiple dimensions, starting with the inputs, followed by the processes, and concluding with model outputs. The third and final section discusses the process of uncertainty quantification that was followed. In particular, details are provided regarding the sensitivity analysis that was performed to examine uncertainty in model parameters and outcomes. Together, verification, validation, and uncertainty quantification provide a holistic evaluation of the adequacy of the model and the uncertainty surrounding the results.

Verification

Two steps were taken to verify the model. First, programmatic testing was performed to ensure the accuracy of the code. Several different approaches were used to evaluate different aspects of model veracity. For example, unit tests were performed by incorporating functions into the model that examined the function output. If any outputs were not as expected errors were generated. Debugging walkthroughs were also performed. I went through each step in the model and examined both the translation into code and whether there were any errors (bugs). For example, the model was examined on a step-by-step basis and compared to the expected behavior as denoted by the theory. Further, where possible, function outputs were validated outside of the modeling environment, and then the model output at each step was compared against the comparator.

Second, test cases were assessed. Two different forms of test cases were used. First, extreme values were used for each parameter to determine whether the model was able to perform as expected. Then, scenarios were examined to determine if the model produced the expected output. For example, under conditions that would undoubtedly produce consensus (i.e., fully connected network; high tolerance thresholds), did the model produce consensus?

Table 6.1

Model Evaluation

Test	Questions answered	Method
Verification		
Programmatic Testing	Does the agent-based model faithfully represent the verbal theory? Are there any errors or misinterpretations?	Unit tests, code walkthroughs, debugging walkthroughs, testing.
Validation		
Calibration	Can parameter values be identified that reproduce the observed data?	ABC
Posterior-predictive checks	How well does the model identify parameters when used against ground-truth values?	ABC
Cross-Validation	What is the predictive validity of the model?	K-fold, classification
Coverage	Is the data of sufficient quality to estimate parameters?	ABC
Model Selection	Could a simpler model explain the phenomenon just as well?	ABC
Predictive Validation	Does the model predict the trajectory of strategic consensus out of sample?	Monte-Carlo simulation
Uncertainty Quantification		
Sensitivity Analysis	How should we interpret the results in the presence of uncertainty? What factors might influence the findings?	Variogram analysis of response surfaces

Validation

Calibration

The goal of model calibration is to identify values of the model's parameters that replicate observed data. The logic behind this process is that if certain parameter values are transformed into observations that are like what might be expected in the real system under investigation, then the theorized process causing this transformation is plausible.

Both frequentist and Bayesian statistics are based upon what are called likelihood functions. In brief, these functions play a critical role in defining the probability of data. However, in some circumstances, such as when there is very limited data, this likelihood function is unknown and/or intractable. As a solution, a synthetic likelihood can be created. This is the goal of Approximate Bayesian Computation (ABC). There are several different forms of ABC, ranging from the most simplistic (rejection sampling), to more advanced methods (Markov Chain Monte Carlo). For the present model, rejection sampling was used.

The general process of ABC rejection sampling is provided in Table 6.2 below and visual representation is provided in Figure 6.1. From a technical standpoint, ABC with rejection sampling proceeds by first developing a set of prior distributions of the model parameters. In other words, the modeler leverages qualitative and quantitative data from past research to make an educated guess about the domain of the various theoretical factors that drive the phenomenon of interest. This domain is then quantified by creating a probability distribution of the entire range of possible values for each parameter.

Table 6.2

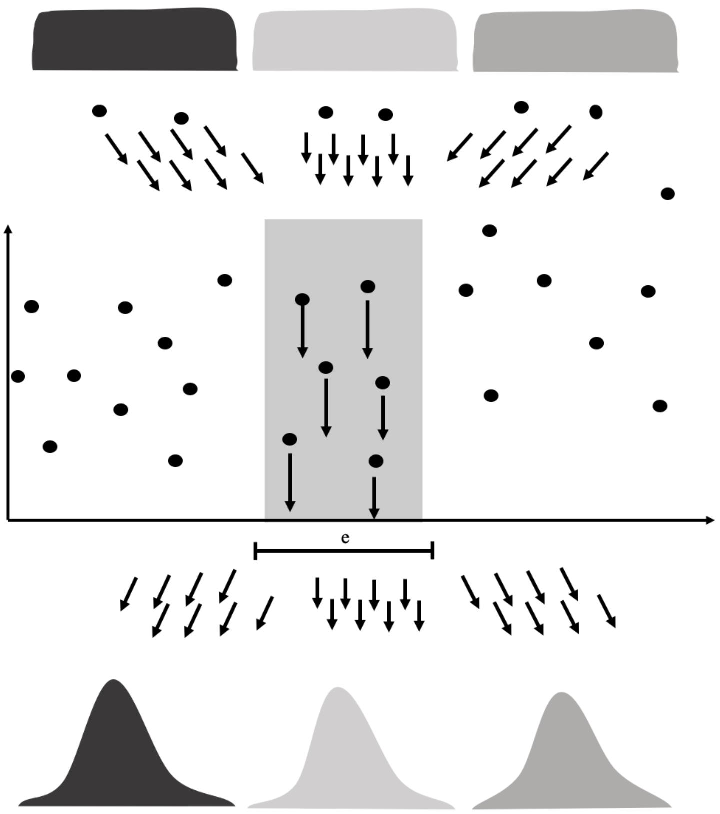
A brief summary of the ABC procedure

1. Randomly sample parameter values from the prior distribution
2. Obtain simulated summary statistics by running the model with simulated data
3. Give every pair of simulated data and simulated descriptives a weight based on the euclidean distance between the simulated statistics and real statistic.
4. (Optional additional step) Fit a local linear or non-linear regression to the accepted samples from the priors to estimate values with no residuals.

While Bayesian statistics is beyond the scope of this paper, what is important to convey is that the modeler can incorporate their uncertainty about parameter values into these estimates. For example, uninformed or weakly informed priors can be used, whereby it is stated that the entire range of the parameters are possible, and further, that each value is equally probable (a uniform distribution). A slightly stronger prior might restrict the range of possible values, but not discuss the probability of those values. Doing so acknowledges uncertainty, as well as the modeling process, or the fact that the current parameters can be refined, and further empirical data can be incorporated through iteration. As empirical data continues to be incorporated into the model, priors become more informed, reducing uncertainty, and providing more accurate estimates.

Figure 6.1

Illustration of Bayesian ABC Rejection Sampling



Note: Uniform priors are specified for each parameter. Values are then repeatedly and randomly drawn from the priors and used in the model to create simulated data. Summary statistics are calculated on the simulated data and compared to summary statistics from the observed data. If the statistic is within a certain range of the observed (e), the point is retained. The accumulated points after a number of runs are used to construct the posterior distribution of the model parameters.

Once priors have been established, parameter values are simulated from the distributions through random sampling, establishing the initial parameters for the ABM. Then the parameters are used to simulate data. Summary statistics defining important patterns in the simulated and observed data are chosen to serve as the criteria for determining how closely the model replicated the observed data. To account for uncertainty, many replications of the model are run to adequately sample the posterior. After a certain number of simulations have been run, the summary statistics of the simulated data are then compared to the observed summary statistics on a run-by-run basis. Parameter values that were able to replicate the observed data (according to the modelers standard) are retained and form the posterior distribution. The posterior distribution reflects the incorporation of new knowledge (empirical evidence) into our previous knowledge of the parameters under study (the prior distribution).

While conceptually ABC is an extremely powerful tool, there are important considerations when using this method as opposed to others, such as genetic algorithms. First, getting an accurate approximation of the posterior is computationally expensive, often requiring thousands to millions of iterations. This is perhaps the primary reason for the limited use of ABC for calibration. Second, the modeler must make several critical decisions. These decisions include how many simulations to run and accept, how to determine the similarity between the simulated and observed data, and whether to use any corrections.

For the present model, weakly informed uniform priors based upon empirical data, literature, and past models were used. All distributions were assumed to be independent. The choice was made to use weakly informed priors to test values in support of the propositions while also accounting for the high amount of uncertainty as a result of limited data. A Latin hypercube sampling (LHS) design was established whereby the multivariate continuous parameter space was divided into 1,000,000 equally spaced points. By doing so, it is possible to examine the entirety of the model's behavior by systematically sampling from the entire parameter space without replacement. Simple random sampling does not ensure that the range of possible conditions are examined and with numerous categorical variables, or all continuous variables, systematically searching the parameter space is infeasible. 72,000 iterations of the model were run for the final estimates. This number was used because as the number of iterations approaches 100,000, the returns in terms of reduced error greatly diminish, meaning the use of extensive time and resources for little improvements in estimation (Li & Fearnhead, 2018).

For each iteration, a random point was drawn using LHS, and this point determined the values of each parameter. Each model was run until consensus was reached (i.e., the sum of differences in updates to opinions of strategic priorities were less than 10^{-5} for 10^{2} timepoints) or the stopping condition was met (10^{5} timepoints). A stopping condition was necessary to prevent the model from running indefinitely, should the conditions allow for it. For the ABC, a tolerance of (.05) was used to reduce the computational burden and avoid monte-carlo sampling error (Li & Fearnhead, 2018). The choice of tolerance was ultimately found to be robust (see Figure 6.3). The observed statistics used to inform the priors and serve as the objective criteria were calculated across four different organizations.

The mean and range of these values were then used for the model. There were six summary statistics that were used for the model. Two statistics were picked for each level of analysis. It is important to identify patterns that represent distinct parts of the system, but not too many to over parameterize the model. Given the primary importance of consensus for the model, consensus was studied at the three present levels of analysis. Specifically, the mean agreement between strategic consensus mental models and respective standard deviation were used. Consensus was calculated as the pairwise Euclidean distance between vectors of strategic priorities. Consensus was calculated between all possible pairwise comparisons and the mean of all of the distances was calculated. All model parameters were standardized prior to performing the simulations. After the model runs were completed, the values were adjusted using a neural network with 12 intermediaries. The purpose of the regression adjustment is to correct for the fact that the accepted parameter values are not exactly equal to the standard value, and this error can propagate throughout the results. Given that model results are typically non-linear in nature with complex interactive components, alternative forms of regression adjustment beyond simple regression are commonly used. Critically, research on ABC suggests that neural network adjustment allows for more precise estimates with fewer iterations (Grazian & Fan, 2020). Once the parameters have been adjusted, the Euclidean distance between the set of parameters for each run of the simulation and the observed statistics was calculated. Given the set tolerance (.05), The runs were then weighted based on their distance using an Epanechnikov kernel. Finally, after the runs had completed, the top 5% of runs (~3600) were retained as the posterior estimates.

Defining the parameter space

Parameter values were chosen to the extent possible based upon quantitative or qualitative information collected through previous research on SLS. This data was supplemented with information from past research that could be used to develop a greater sense of the form of the model parameters. For any parameters with little or no pre-existing information, a uniform distribution spanning all possible values was used. There was not sufficient data to provide distributional properties of the priors, so only the range of possible values was changed, and uniform priors were used throughout. It is important to note that while the specification of priors is important, in most circumstances, misspecification only increases the time it takes for the model to converge and does not greatly influence model accuracy. The prior distributions used for calibration, as well as the sources from which they were derived, are listed in Table 6.2.

Table 6.2

Model Parameters

Definition	Form	Values	Sources
Number of Groups	Informed	(11)	Empirical Data
Group size	Informed	(6)	Empirical Data
Intra-team density	Weakly informed uniform	(.15, .60)	Empirical Data; (Zhang, Zhang, & Danziger, 2020)
Inter-team density	Weakly informed uniform	(.05, .20)	Empirical Data; (Zhang, Zhang, & Danziger, 2020)
SLS centralization	Weakly informed	(1, 30)	Yamanoi & Sayama (2013)
Team centralization	Weakly informed	(.1, 5)	Yamanoi & Sayama (2013)
ELT trust preference	Weakly informed	(.02, .8)	Theory
MM trust preference	Weakly informed	(.02, .6)	Theory
Link decay rate	Uninformed	(.02, .1)	(Yamanoi & Sayama, 2013)
Link-formation rate	Uninformed	(.01)	(Yamanoi & Sayama, 2013)
Link-severance rate	Uninformed	(.01)	Lin & DeSouza (2013)
Influence salience	Uninformed	(0, 1)	Lorenz (2022)

Definition	Form	Values	Sources
MM tolerance	Weakly informed	(0, .5)	(Yamanoi & Sayama, 2013)
ELT tolerance	Weakly informed	(0, .4)	(Yamanoi & Sayama, 2013)
Team salience	Uninformed	(0, 1)	Empirical Data
ELT salience	Uninformed	(0, 1)	Empirical data
CEO salience	Uninformed	(0, 1)	Lorenz (2022)
Initial opinion distribution skew	Uninformed	(.5)	N/A
Initial opinion distribution width	Uninformed	(.5)	N/A
MM learning	Weakly informed	(.2, .8)	Lorenz (2022)
ELT learning	Weakly informed	(.1, .5)	Lorenz (2022)
Tolerance scaling factor	Uninformed	(1, 10)	N/A
Trust scaling factor	Uninformed	(.02, .1)	N/A

To obtain prior estimates from empirical data, summary statistics were obtained from variables that reflected the model parameter across four organizations. During each data collection, SLS members were asked to answer self-report items regarding their strategic communication networks and strategic priorities. To provide their strategic priorities, a list of organizational strategies was provided that was developed alongside organizational stakeholders prior to administration. Respondents then rank ordered these priorities. Participants also were provided with roster style sociometric items. In the context of strategy, they were asked to identify organizational members who they interacted with about strategy formulation and implementation (each separately). For the present model, strategy formulation conversations were used to create the strategic communication networks in the model. For example, self-report measures of strategic communication networks were used to calculate densities within departments as well as across the SLS. The average density as well as the standard-deviation of the densities was then obtained from all the data collected. To construct the parameter range then values at the lower and upper bound were chosen that were at least 2 standard deviations away from the mean to account for the uncertainty in prior estimates. For variables that were to be estimated, empirical data was used to define the parameter ranges of intrateam density, inter-team density, within-team strategic communication centralization, between-team strategic communication centralization. Certain fixed factors in the model were also derived from the data such as the number of groups in the SLS, the size of each group, the size of the TMT, and the hierarchical structure.

For all parameters, even if data was available, information from previous research was also examined to determine the values of the priors. For example, previously validated models that have used similar parameters and meta-analyses were used to identify potential values. Finally, practical considerations were considered. More specifically, the parameters were restricted to not take on unrealistic values. For example, while a network density of 1 is mathematically feasible, it is not a realistic value. All parameters that were used for calibration of the model were also subject to sensitivity analysis to determine the influence of the choice of the prior on model outcomes, as well as to identify factors that should be fixed in future research.

Parameter fitting

A total of 76,746 iterations of the model were run. Several acceptance values were tested including (.001, .05, .1) and compared to find the best fit. Ultimately, .05 was used which resulted in a final sample of 3,260 parameter sets.

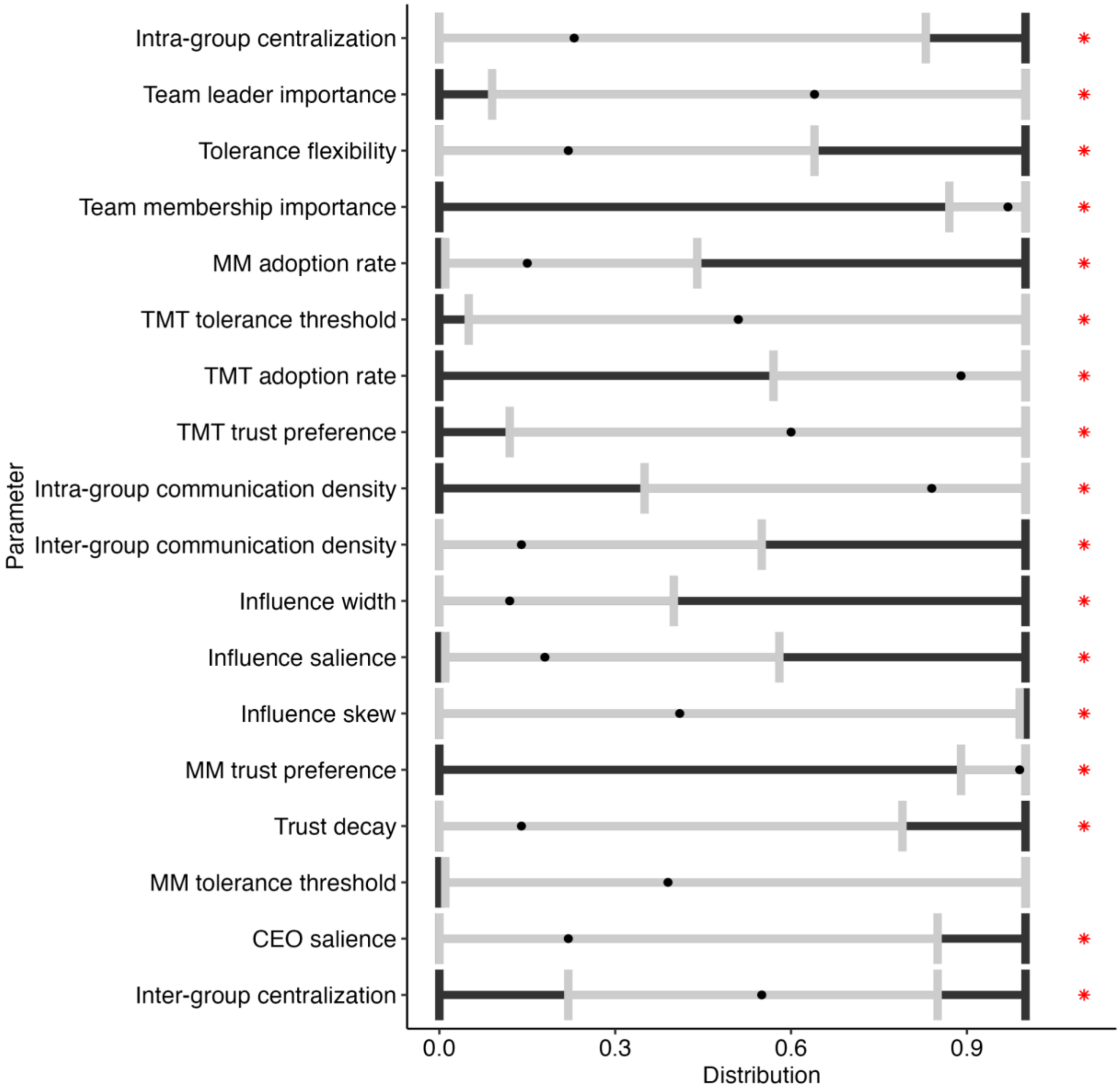
Parameter estimation

The estimated posteriors from the ABC estimation procedure are shown in Figure 6.2 and are outlined in Table 6.3. An issue with computational models is that to achieve the specified simulation criteria, the sample size may have to be set to extraordinarily high values, therefore making standard statistical tests invalid. To test whether the posterior significantly narrowed as compared to the prior distribution, Levene's test (a model free test for equality of variances) was performed with a Holm correction for repeated assessment. The results demonstrate that all but one parameter (MM tolerance) were significantly refined ($p < .01$) as a result of the ABC estimation.

The comparison between the prior distributions and the posterior distributions is shown in Figure 6.3. Also shown in Figure 6.3 are tests of robustness of the ABC estimates to changes in the type of ABC estimation and the tolerance value used. Specifically, the parameters were also calibrated using ABC with tolerances of .1 and .001, as well as using rejection sampling and loclinear regression. The results suggest that the estimated values are generally robust across form of estimation and tolerance level. To investigate the accuracy of the estimation procedure, two separate tests were performed; cross-validation, and coverage.

Figure 6.2

Prior and Posterior Distributions



Note: 95% HDI estimates of posterior distributions for each parameter (gray), compared to prior distributions (black). The black point represents the median value. Significant change in the distribution was evaluated with Levene's test with a Holme correction for repeated assessment. Parameters that significantly (p < .05) changed from the prior are marked with a red asterisk.

Posterior Predictive Checks

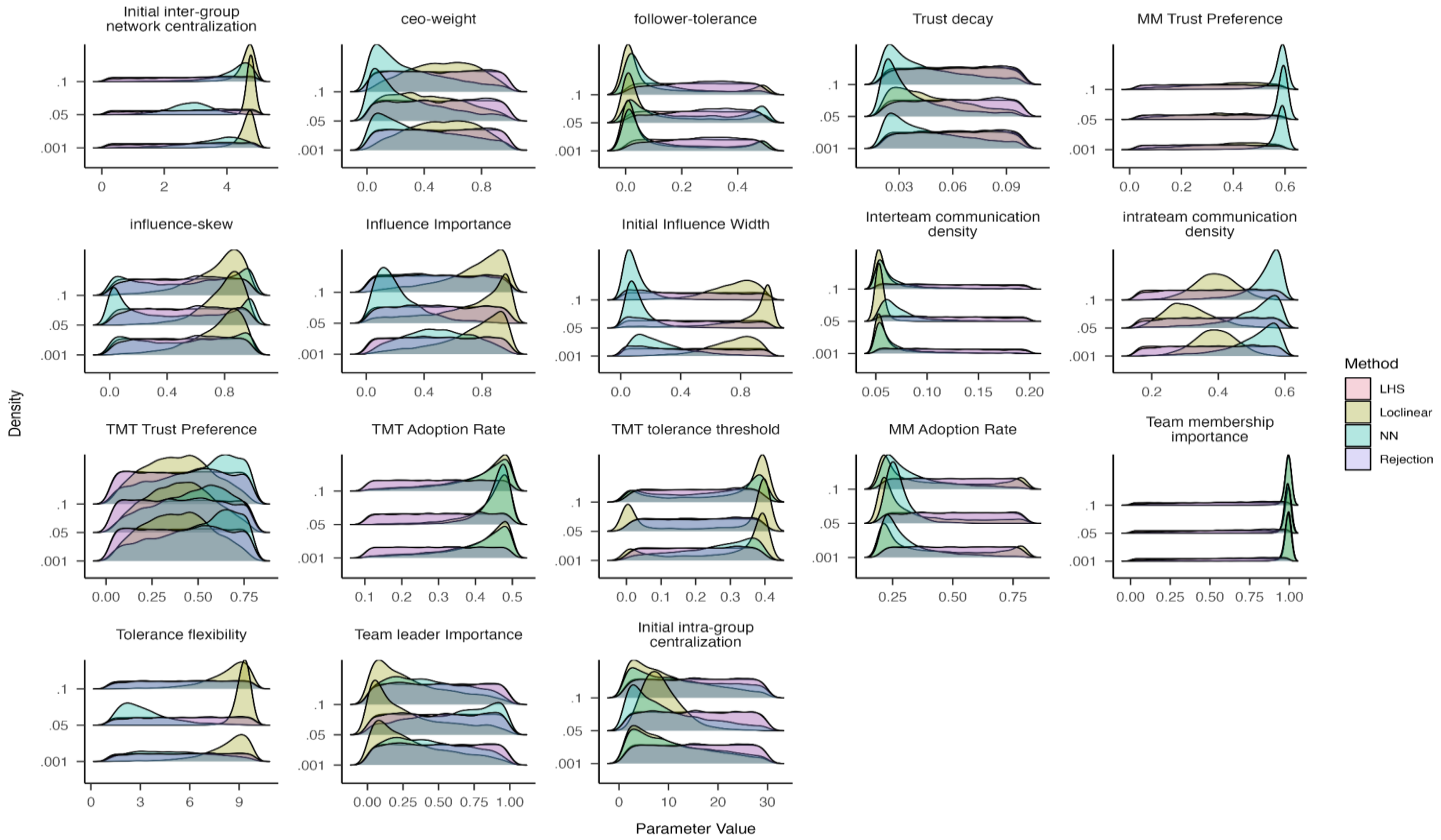
For the posterior predictive checks, the distribution of model outcomes for the accepted runs from the calibration were formed and plotted against the observed values. As shown in Figure 6.4, The model was able to well capture the group and system strategic consensus, as well as the variance in the system consensus. The consensus within the ELT and variance in group and ELT consensus were also captured, but to a lesser degree.

Coverage

The coverage property is a test evaluating the accuracy of the posterior distributions (Prangle, 2014; van der Vaart et al., 2018). Specifically, to establish confidence in the results of the analysis, it needs to be demonstrated that the ABC algorithm was able to search the entire range of the prior distribution. If there are areas of the prior distribution that were not examined, then confidence in the posterior estimates is diminished. In order to test the coverage property, the following procedure was followed. First, a random output was sampled from the posterior distribution. Then, ABC was performed using the output of the draw as pseudo-data (i.e., target value) and the original 72,000 runs of the model as the simulated data. The accepted runs therefore reflect the number of runs associated with that particular accepted outcome for each parameter. This procedure was repeated 100 times. Finally, the accepted runs were used to calculate the proportion of accepted parameter values that are less than what produced the value from the pseudo-data for each parameter. To meet the conditions of the coverage property, the distributions of the proportions for each parameter should be uniform, which demonstrates that the posterior estimates for each parameter are based on the entire range of the prior. Figure 6.5 shows the results of the coverage test. The distributions appear roughly uniform indicating that the estimated posterior distributions are accurate.

Figure 6.3

Parameter Estimates



Note: LHS = latin-hypercube sampling. NN = neural network. LHS represents the prior distribution. All other distributions represent other estimation methods. As a test of robustness, 3 different tolerance levels were used to calibrate the model (.1, .05, .001).

Table 6.3

Posterior Estimates

Parameter	Median	MAD	M	SD	MAP
System strategic communication centralization	4.99	0.01	4.97	0.10	4.99
CEO salience	0.18	0.21	0.28	0.27	0.02
Middle manager tolerance	0.28	0.15	0.28	0.13	0.31
Tie decay	0.03	0.02	0.04	0.02	0.02
Middle Manager preference for trust	0.09	0.06	0.12	0.10	0.05
Skew of initial influence	0.86	0.15	0.78	0.22	0.98
Influence salience	0.74	0.27	0.68	0.26	0.96
Spread of initial influence	0.98	0.03	0.94	0.09	1.00
Interteam strategic communication density	0.09	0.04	0.10	0.04	0.06
Intrateam strategic communication density	0.51	0.06	0.49	0.07	0.53
TMT preference for trust	0.03	0.01	0.06	0.08	0.02
TMT learning rate	0.49	0.01	0.48	0.02	0.49
TMT tolerance	0.13	0.17	0.16	0.14	0.00
Middle manager learning rate	0.50	0.15	0.50	0.14	0.52
Team salience	0.88	0.11	0.84	0.15	0.97
threshold-temperature	3.28	2.08	3.84	2.19	1.76
Team leader salience	0.46	0.37	0.47	0.29	0.07
Within-team strategic communication centralization	17.49	10.49	16.87	8.20	27.39

Note: MAD = mean absolute deviation, M = mean, SD = standard deviation, MAP = maximum a posteriori probability estimate

Figure 6.4

Estimated outcome densities and empirical values

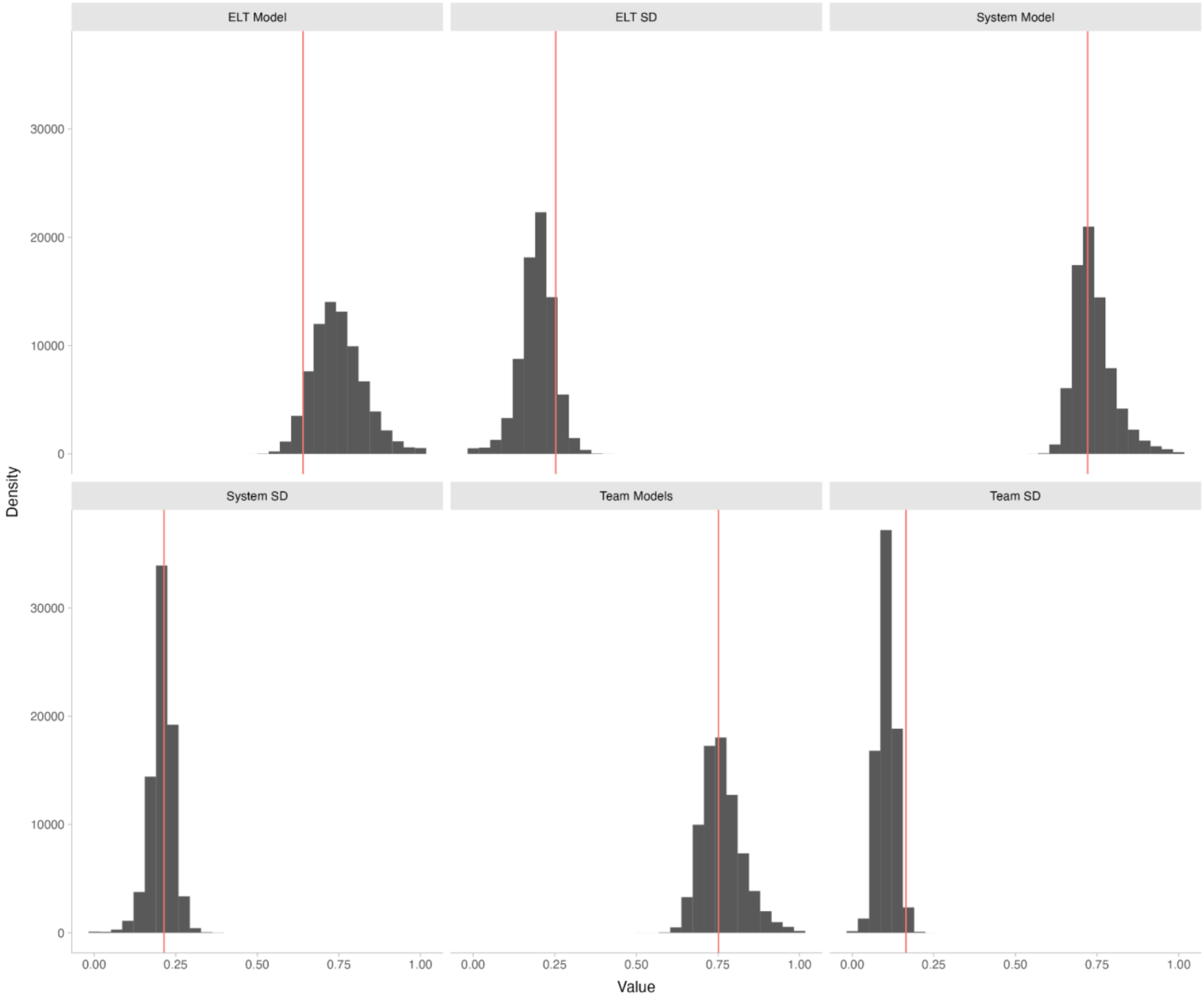
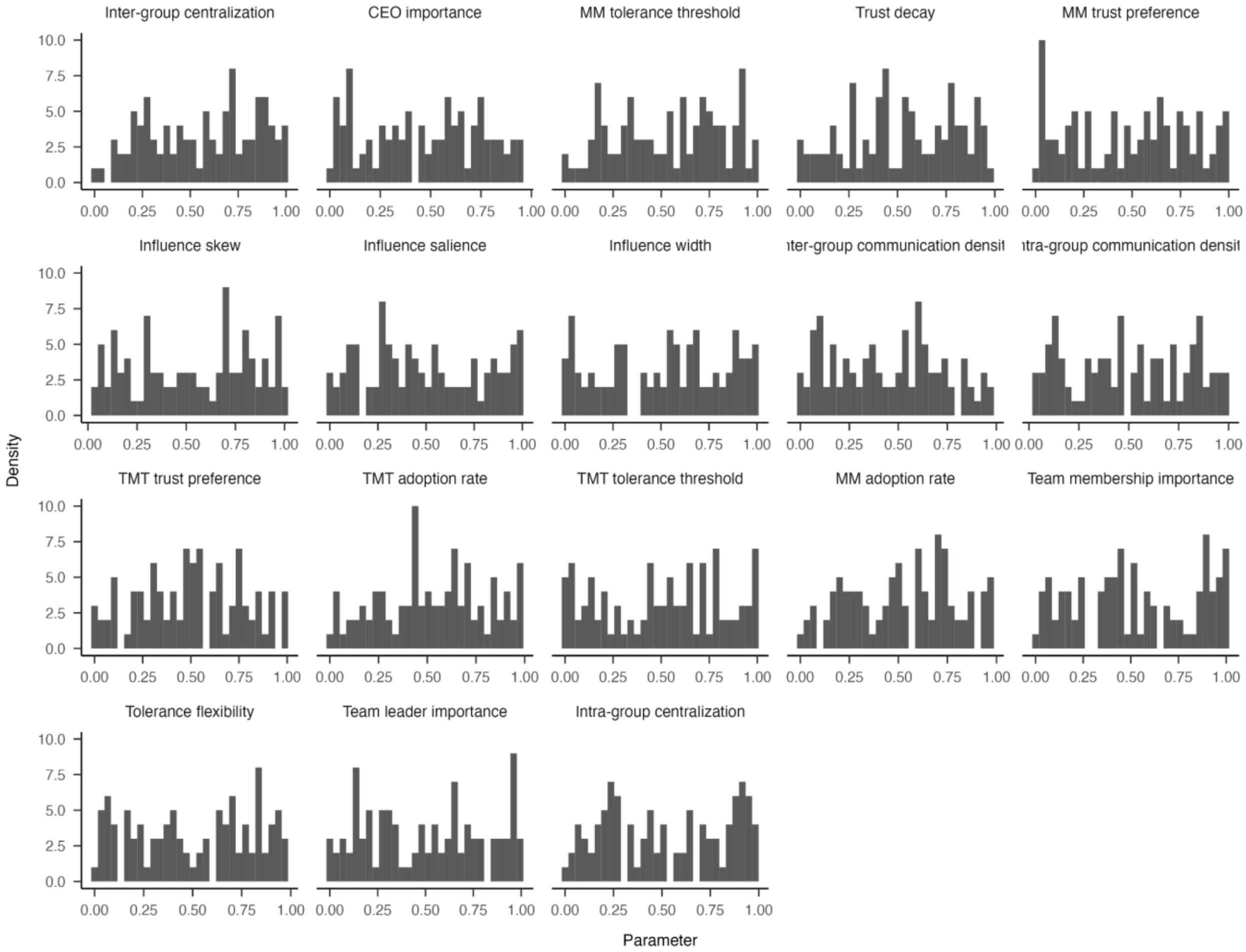


Figure 6.5

Coverage for parameter estimation



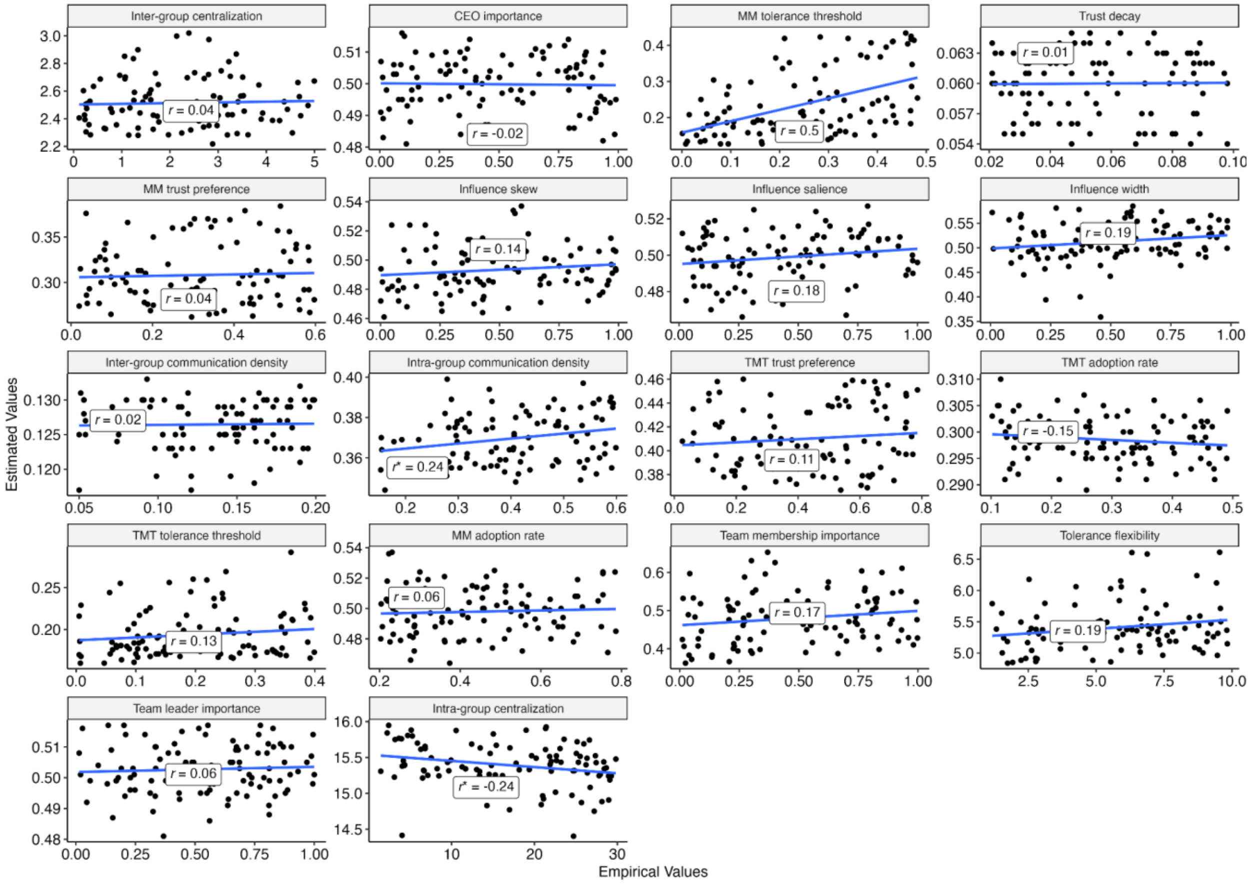
Note: Distributions represent the percent of values that fell below the parameter's empirical value.

Cross-Validation

To cross-validate the model, k-fold cross-validation was performed. K-fold is a popular method of model validation in data science. The benefit of k-fold cross validation is that the model can be compared against data where the “true” values are known. The true values are known because data is used to predict a subset of itself, with known values. As such, the accuracy of the model can be evaluated precisely. To perform a k-fold cross validation, the number of repetitions (*k*) is determined. For each *k*, one datapoint is removed from the dataset and used as the pseudo-data. The remaining data is then fed into the model to predict the pseudo-data. This process repeats k times up to *n* - 1, which is referred to as leave-one-out (LOO) cross-validation. While more repetitions provides more robust results, increasing the number of iterations comes at a computational cost. To balance robustness of results and computational cost, a relatively large number (100) was used. First, 100 rows of data were taken from the accepted values of the calibration procedure to be used as pseudo-data. Then, the remaining data was used to predict the pseudo-data. Specifically, ABC was performed with a neural-network post-adjustment and the best fitting estimates were retained using the same tolerance level from model calibration (.05). As shown in Figure 6.6, many of the parameters were not adequately estimated in the cross-validation. Only two parameters were estimated well by the real and simulated data (intra-group communication density and intra-group centralization). 13 parameters were estimated well from empirical data but not the simulated data, and one parameter was not estimated well from either empirical or simulated data.

Figure 6.6

Posterior Predictive Tests



Note: Each facet shows the correlation between actual values accepted from the calibration procedure, versus k-fold estimated values. Significant p-values (p < .05) are marked with *.

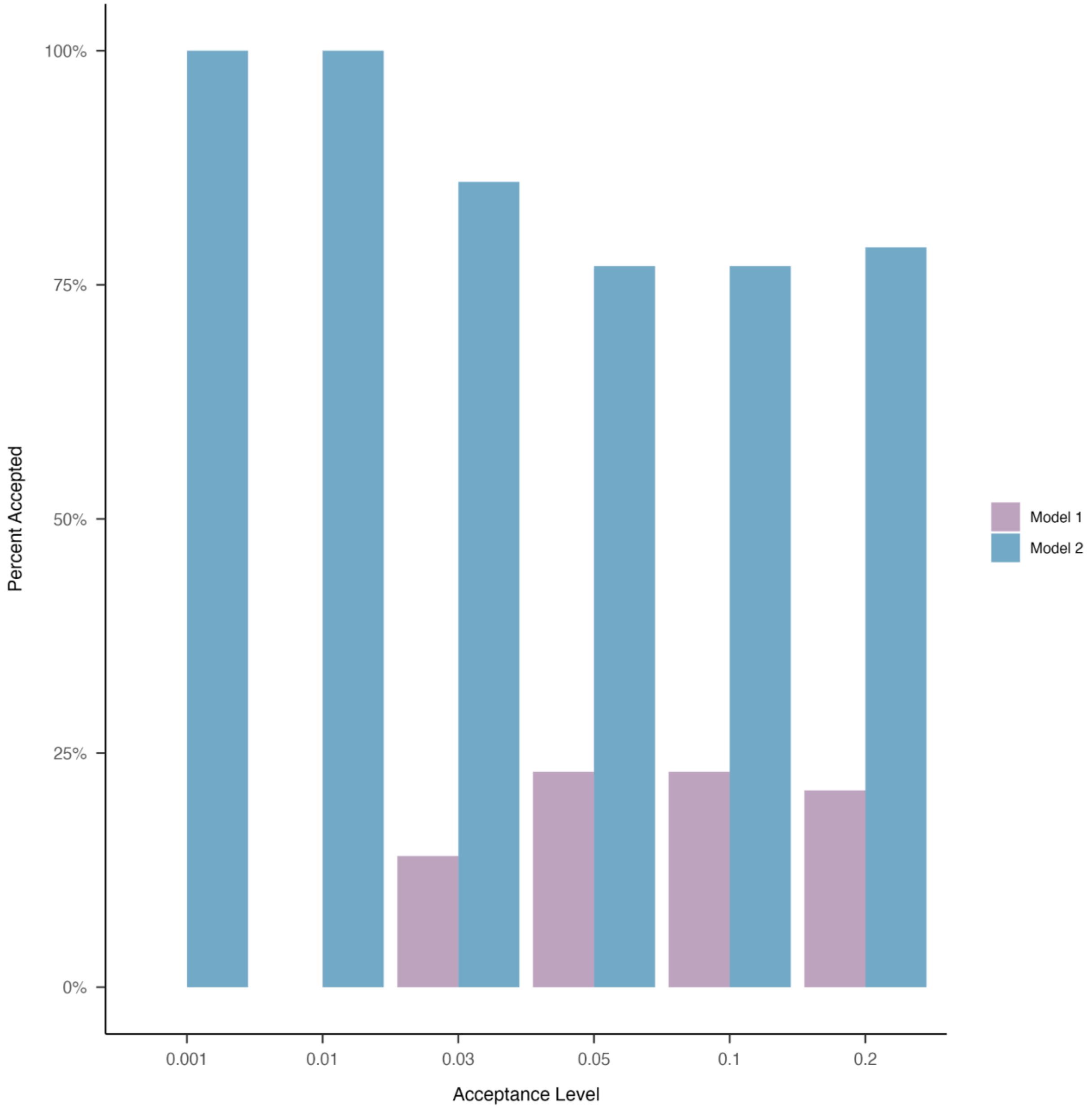
Model selection

An important consideration with modeling is that the simplest possible model is used in order to evaluate the phenomenon of interest. This is to ensure that there aren't confounding and/or unnecessary processes and/or parameters in the model. To this end, model comparisons were performed between the current model and a simplified model reflecting how currently consensus is studied. The reduced model consisted of only the structural features (density, centralization, group size, number of groups) and a uniform tolerance and learning parameter.

This model was then subject to ABC under the same protocol as that used for the full model. In particular, the model was run 72,000 times, with a tolerance of .05, and a neural-network adjustment using 100 runs with 12 nodes. The accepted runs of both the full model and reduced model were then combined and ABC was performed on the entire dataset. The reasoning behind doing this is because the ABC procedure identifies the best fitting model runs for the observed data. Thus, the ABC procedure was used as a classification task where the number of runs that were accepted in the results coming from either the full and simplified model were calculated and compared. Several tolerance levels were tested as a robustness check. The results of the model comparison are shown in Figure 6.7. The results demonstrate that across tolerance levels, the ABC procedure predominantly selects runs from the full model, having never selected the full model any less than 75% of the time across tolerances. This suggests that the results produced by the full model provide a closer fit to the observed data than the reduced model. This supports the added complexity of the full model.

Figure 6.7

Model Selection



Predictive Validity

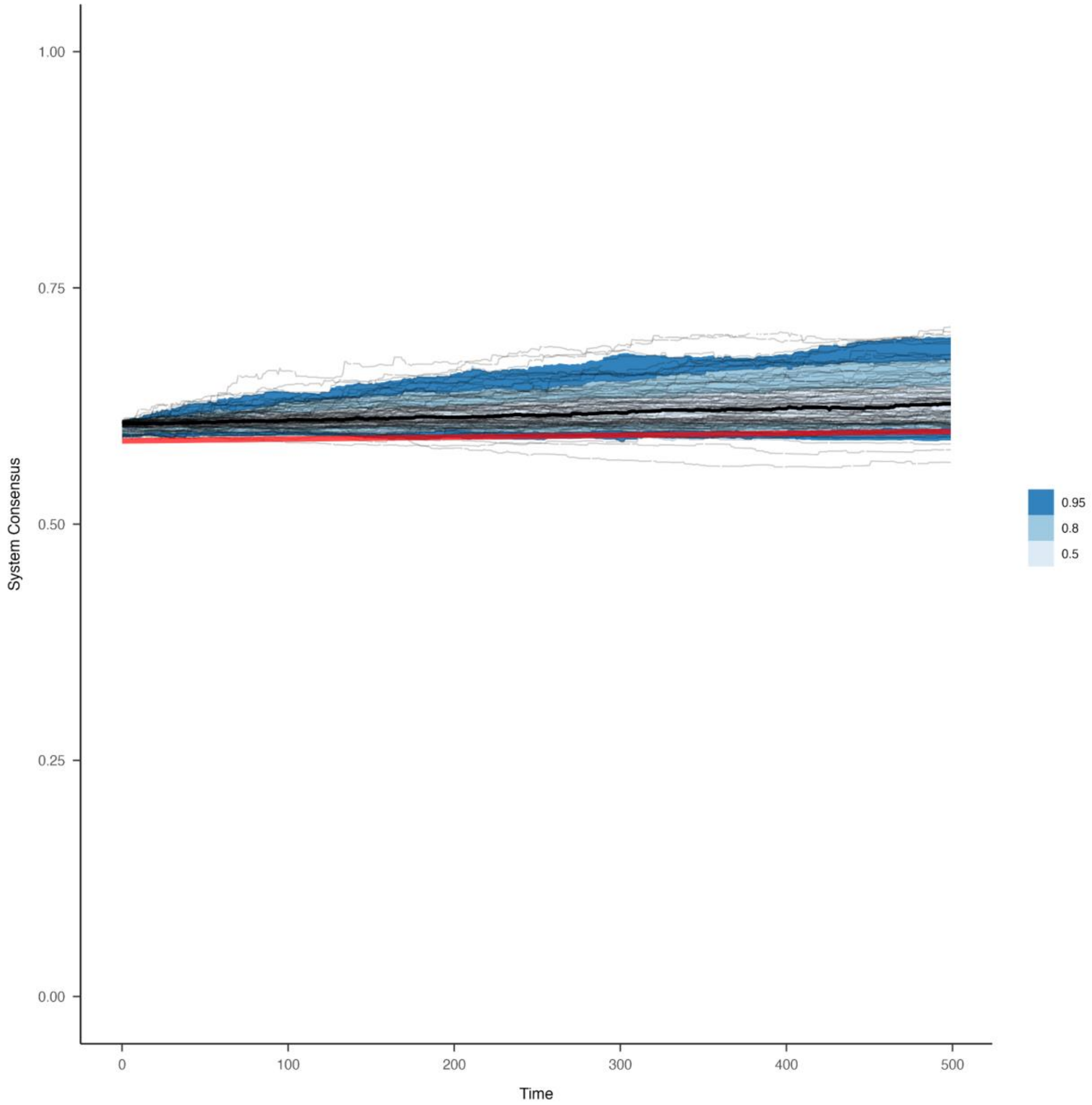
To assess the predictive validity of the model, parameters extracted from a new dataset with data collected at two timepoints were used in the model. The model was run 100 times and 95% confidence intervals were calculated around the mean model estimate. A burn-in procedure was used to run the model such that random network initializations were iterated through until a random structure was found that created an initial consensus that was >= .01 of the observed consensus. The reason for doing so is that the starting consensus in each network cannot be predicted given its dependence upon the pattern of initial relationships. The results of the predictive test are displayed in Figure 6.8. The results demonstrate that the trajectory of strategic consensus development within a new organization follows that predicted by the model, as it falls within the 95% confidence interval.

Sensitivity Analysis

The goal of sensitivity analyses is to determine the importance of model parameters through their influence on model output (Lee, 2015). For example if different levels of a particular parameter do not cause variability in the model output, then it can be said that the model is not sensitive to the parameter and the value can most likely be fixed at a certain value or removed from the model. Alternatively, if the levels of a certain parameter cause significant fluctuations in the output of the model, then the parameter can be said to be influential and therefore should be examined further.

Figure 6.8

Model Prediction



Note: Mean simulation run is indicated by the bold black line. The 95% confidence interval of the 100 simulation runs are indicated by the dark blue. Light grey lines represent each run within the ensemble. The red line is the observed data from the validation sample.

Variogram analysis of response surfaces

To examine model sensitivity I used a method called variogram analysis of response surfaces (VARS). Briefly, VARS was chosen over other more popular methods because it, 1) is able to approximate both derivative and variance based sensitivity indices (i.e., Sobol indices, and Morris elementary effects), and 2) may be more computationally efficient. In order to perform the VARS, a new simulation was performed. First, the dataset had to be created so that the data points that were collected were located at the correct point in the parameter space for the VARS. To ensure the sample was appropriate I used a method of sampling called star sampling.

Sampling. Star sampling in its simplest form is conducted by choosing a random number of points (called star centers) from within the multidimensional space. Then, for each parameter, values are equidistantly sampled along a vector (see Figure 6.9). 50 star centers were used for the current sensitivity analysis, with a distance of (h = .1). This means that for each star center, all model parameters were measured at 10 points, each one .1 standardized units away from the previous.

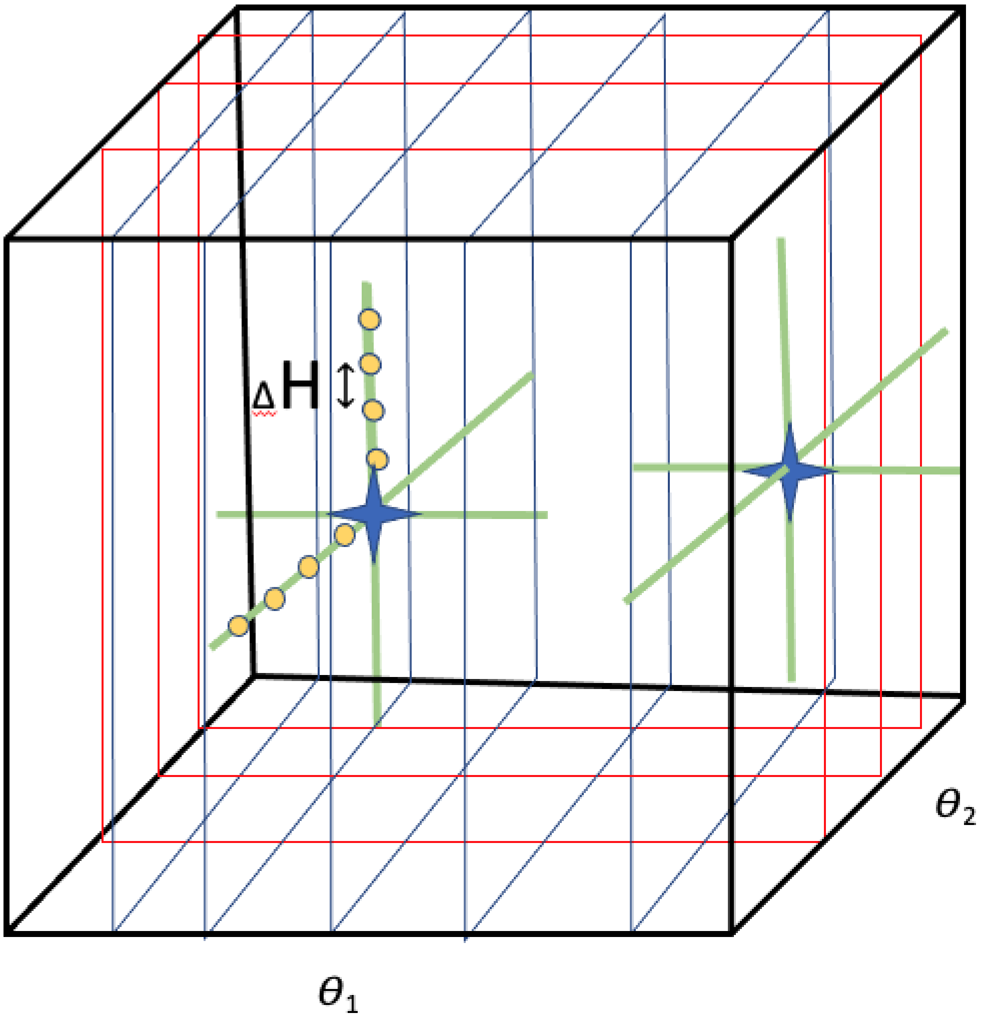
Procedure. Running the sampled parameters through the model and associating those points with model outcomes, the response surface of the model was investigated through a variogram. The variogram was analyzed further to calculate Sobol total-order effect indices, Morris elementary effects, and integrated outputs that summarize parameter sensitivity across different perturbation scales (i.e., integrated variogram analysis of response surfaces or IVARS). The three indices complement one another allowing for a complete picture of global model sensitivity. The 50 star centers yielded a matrix of 9,000 iterations of the model. During each iteration, a focal parameter was varied, while the other parameters remained constant at the estimated value from calibration. The results were then bootstrapped to create 95% confidence intervals with 100 repetitions.

Measures. Strategic mental models were used as the outcome of the model runs used for sensitivity analysis. At the end of each simulation, the agreement between every agent's mental models was calculated as the distance between their models which were represented as single floating-points. The distances were then used to calculate the average agreement within each group, and within the system as a whole. Sensitivity was then assessed based on these values.

Results. The results of the sensitivity analyses are reported in Figure 6.10. As shown, inter-group communication density, influence salience, and the width of the influence distribution had the greatest influence on model variability. These results were robust to bootstrapping and the three separate indices. Even so, the three parameters with the strongest relation to model sensitivity were not substantially more important than the remaining factors. This suggests that the model is not unduly sensitive and that no one parameter is of particular importance to model sensitivity. It also provides evidence that model outcomes are reliable and are not the result of degrees of freedom in parameter value selection or otherwise.

Figure 6.9

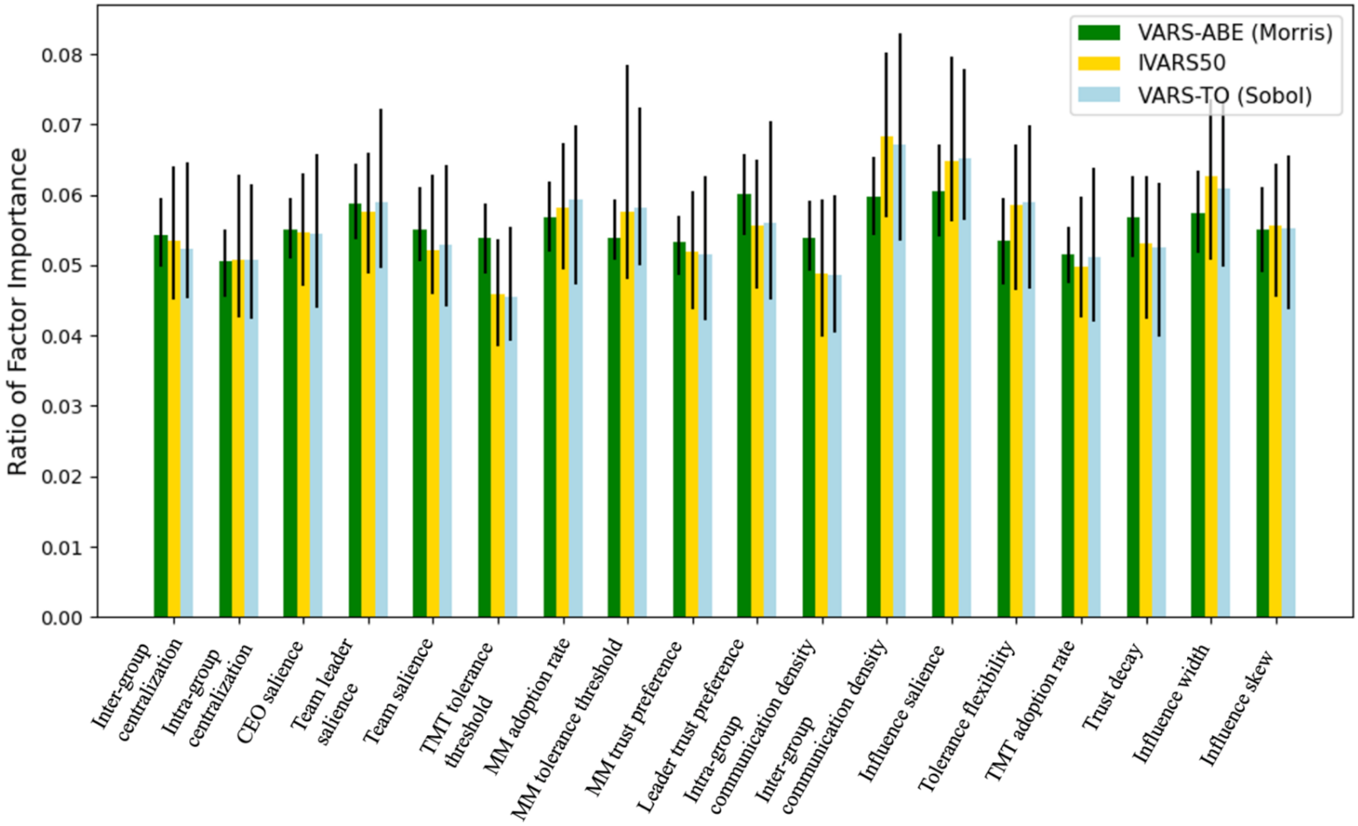
Star Sampling Procedure



Note: Stars represent points sampled through LHS, followed by the yellow points which are points that are sampled systematically n-times at distance H in as many dimensions as there are parameters.

Figure 6.10

Variogram Analysis of Response Surfaces



CHAPTER 7

VIRTUAL EXPERIMENTATION

The primary contribution of this dissertation is to build a ‘virtual laboratory’ (i.e., a computational model) that can be used to test hypotheses about the antecedents of strategic consensus. To demonstrate the viability of this approach, I used virtual experiments to answer two initial Research Questions: RQ1: *What is the impact of initial communication network structures (i.e., communication centralization and density within and across component groups) on emergent patterns of strategic priority perceptions?* and RQ2: *What impact do influential individuals have on eventual patterns of strategic priority perceptions?*

Having qualified the model, the purpose of the virtual experiments was to take a look into the specific effect of initial structural and individual features on the patterns of strategic consensus that emerge. A 5 x 2 factorial design resulting in a total of 32 conditions was used to examine the research questions.

Simulation Settings

Measures

All measures were collected on the strategic communication network structures. Specifically, a semantic network was created (purely for analytical purposes) that mapped the agreement between all individuals in the SLS. This network was updated at every time step and was used as a reference point for calculating the various metrics. It is important to note that two individuals need not share a tie in order to be in agreement.

Number of major vs. minor clusters. The number of major and minor opinion clusters provides a way to evaluate if opinions are polarized, fragmented, or reached consensus. Strategic clusters were identified in the model through the Louvain method. Briefly, the Louvain method attempts to maximize the modularity of the network, or the density of within cluster relationships versus external relationships by first calculating local modularity throughout the network. Then local modules are combined into nodes and this procedure is repeated until modularity has been maximized. Minor clusters were classified as clusters with less than 2% of the total agents, whereas major clusters are those with > 2%.

$$H = -\sum_{r=1}^{K} \frac{Sr}{N} ln \left(\frac{Sr}{N} \right)$$

Shannon entropy. While the number of major and minor clusters can show whether there is fragmentation, quantifying the degree of fragmentation requires a separate metric. For example, while there may be a differing number of clusters, this doesn’t quantify variation in the size of the clusters. Following previous opinion dynamics scholarship (Han et al., 2020; Li & Porter, 2022), Shannon entropy was calculated. Shannon entropy accounts for patterns of consensus by providing a metric of the relative size of clusters. Specifically, holding the number of clusters constant, when opinion clusters are of similar sizes the Shannon entropy value is larger than if there is diversity in cluster sizes. This is due to the fact that there is more uncertainty in cluster membership when clusters are similar in size. Further, when clusters are of similar sizes, entropy is larger if there are more clusters. Across all opinion clusters (K), the proportion of actors that are part of that cluster. Shannon entropy is calculated after model convergence using the major and minor opinion clusters.

Local receptiveness. A possible reason for opinion fragmentation is pseudo-consensus, or the belief that there is a consensus because all current relationships are with people who have similar views. The formation of echo chambers makes it impossible for one's opinion to be changed as they cannot seek out differing opinions. Li & Porter (2022) developed a measure of opinion isolation called local receptiveness. Local receptiveness is a metric that shows the ratio of outgoing connections that are within an actor's confidence bound (Li & Porter, 2022).

$$L_i(t) = \frac{|\{j \in N(i) : |x_i(t) - x_j(t)| < c\}|}{|N(i)|}$$

Where Li(t) is the average local receptiveness of all actors in the network, j is a neighbor of actor (i) where the absolute value of the difference of their opinions is below the opinion threshold of (i), and N(i) is the number of neighbors of (i). The average of local receptiveness of all agents in the network provides a clear indication of the form of consensus and the ability of the network to be open to differing opinions. While there is rewiring in the model, this rewiring is based on strategic homophily and therefore ties are unlikely to spread outside of local clusters. Local receptiveness is calculated after model convergence.

Stopping criteria

The stopping criteria for the model were established in order to quantify when a final state has been reached, such that continued iterations would not provide any further information. I defined the stopping criteria as when an actor could not improve their position through any further action, holding all else constant. In this model, agents are driven to make sense of their environment by surrounding themselves with people who have the same opinion. Once someone is completely surrounded by others with the same opinion, they have reached their maximal position as they cannot be exposed to new information. If every agent is in such a position, then there is said to be a Nash Equilibrium. Nash Equilibria therefore represent a state of consensus, either through a homogeneous view of strategy throughout the system, two opposing homogeneous views (i.e., polarization), or splintered homogeneous views (i.e., fragmentation). The final state was operationalized as when the model had run for 1000 timepoints (i.e., ticks) without change in any agent's opinion. To account for the fact that patterns of stable consensus cannot always be achieved, a trigger condition was specified to unconditionally stop the model after 10^5 iterations.

To determine the number of replications necessary for the results to stabilize ensemble tests were performed (Figure 7.1). The purpose of the ensemble test was to run the model with incrementally more iterations ($t0 \ldots tn$). After each run the coefficient of variation was calculated for that number of time steps for each outcome variable. The minimum number of necessary runs was then identified separately for each outcome as the point where the coefficient of variation dropped below a specified value (.01), and did not increase above it again. The final estimate of the number of runs was then identified as the longest number of runs required for an outcome to stabilize. The results of the ensemble test performed suggested that all model outcomes stabilized after 225 iterations. The second part of the ensemble tests evaluated the amount of variability due to the model itself. To quantify this, specific parameter sets were randomly sampled and each sampled parameter set was run an increasing number of iterations. The results suggested relatively stable patterns within each model as the number of iterations increased, suggesting it was not necessary to replicate the results with multiple random seeds.

Results

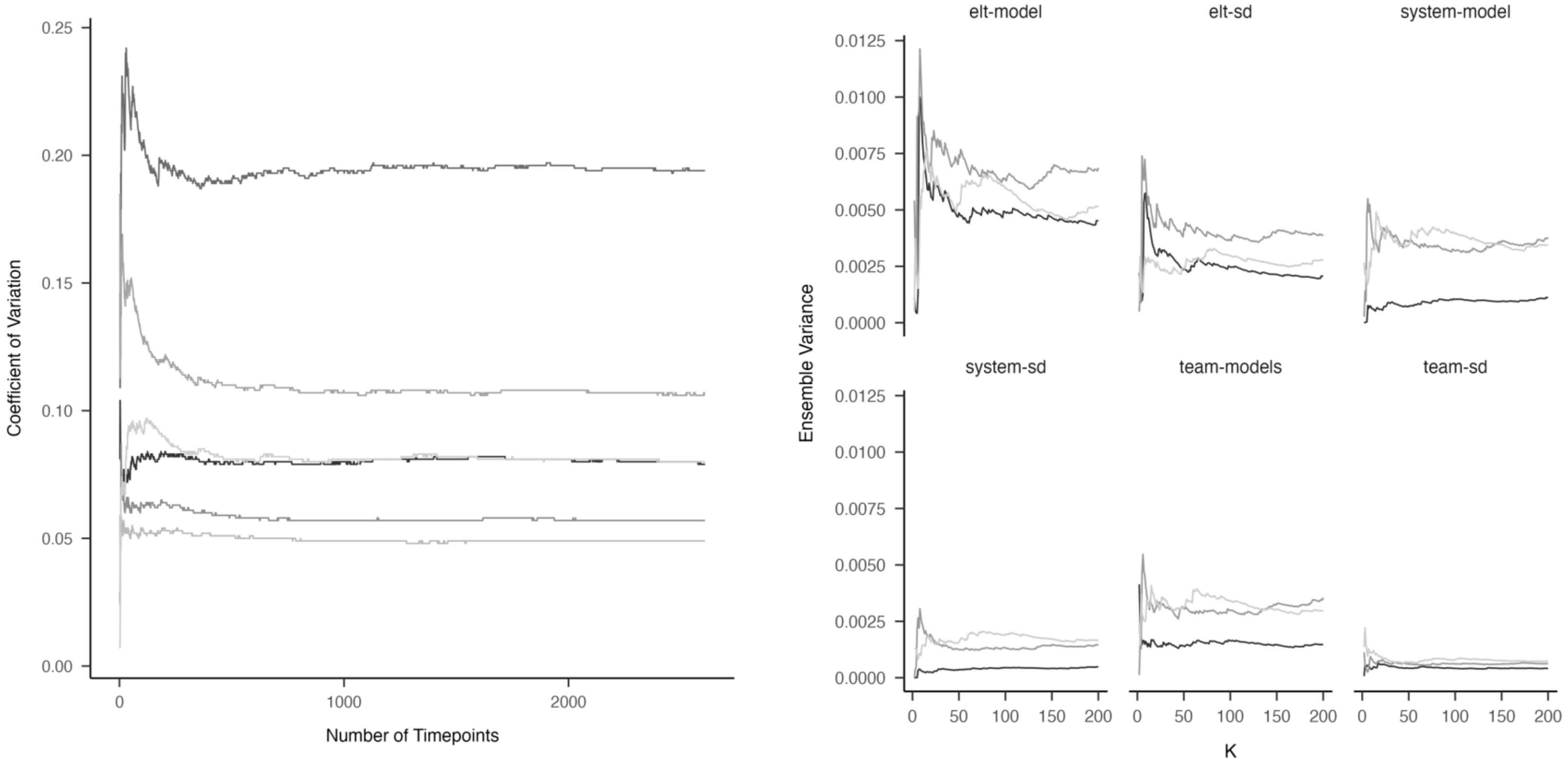
The experiments consisted of a 5 x 2 factorial design. For each SLS, the within and between team network density, within and between team network centralization, and influence were manipulated. Factor levels were selected that represented high and low levels of each factor. The remaining factors were not a focus for answering the research questions and were therefore fixed based on the results of the calibration procedure. Each condition was replicated 225 times in accordance with the ensemble tests (Figure 7.1). Conditions were subsequently compared through marginal means. Results are provided in Figures 7.2, 7.3, and 7.4 with 95% HDIs. All marginal means were compared using the Kolmogorov-Smirnoff test with a Holmes correction for repeated assessments. All results were found to be significant ($p < .05$), and therefore discussion of statistical significance is excluded from the results.

Research Question 1

Research question 1 asked, "*What is the impact of initial communication network structures (i.e., communication centralization and density within and across component groups) on emergent patterns of strategic priority perceptions?*" In the simulated experimental SLS's, strategic communication network density, and within and between group strategic communication network centralization. As can be seen in Figure 7.2, inter-group strategic communication density had the largest impact, with high inter-group density leading to lower levels of entropy. It can be concluded from this result that higher levels of inter-group strategic communication may lead to fewer (and larger) opinion clusters resulting in either polarization or consensus. Alternatively, intra-group strategic communication centralization increased the level of entropy as it increased.

Figure 7.1

Ensemble Models of Uncertainty



Note. (a) shows the length of (model) time required for outcomes to stabilize. (b) shows the number of experimental replications are necessary to achieve stable estimates

Thus, highly centralized groups located within the SLS may create strategic priority perception fragmentation. Both inter-group strategic communication centralization and intra-group strategic communication density had marginal effects on entropy and therefore likely have little to no influence on the disparity in cluster sizes. Figure 7.2 illustrates how the parameters either isolated or exposed SLS members to broader strategic perspectives. Higher levels of intra- and inter-group strategic communication network density were associated with higher levels of local receptiveness. Both forms of centralization did not impact local receptiveness.

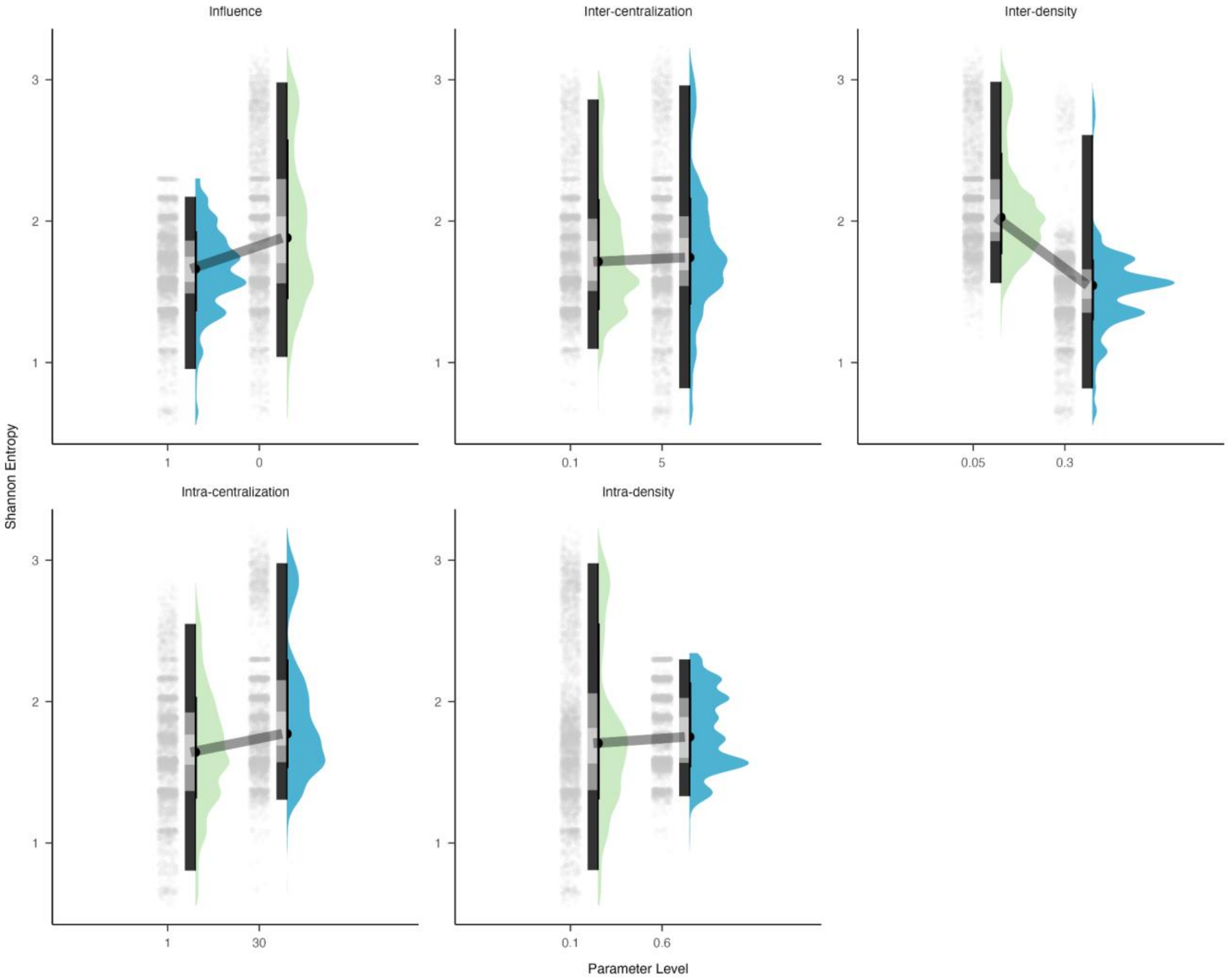
Finally, Figure 7.3 presents the frequency of different major cluster sizes by parameter. First, low inter-group strategic communication centralization was associated with more medium clusters, while high at high levels it was associated with more fragmentation (i.e., many small clusters). Intra-centralization on the other hand, was associated with greater opinion fragmentation at lower levels, suggesting that centralization at the within and between group level may hinder consensus and foster the creation of factions. With regard to density, high inter-group strategic communication density created more large clusters than low density. However, at low levels, inter-group strategic communication density led to more small clusters than higher densities. For intra-group strategic communication density, low densities were related to smaller cluster sizes, with higher densities creating more medium sized clusters and no small clusters. The absence of smaller clusters indicates that intra-group density has a strong impact on the emergence of consensus.

Research Question 2

Research question 2 addressed the question of, "*What impact do influential individuals have on eventual patterns of strategic priority perceptions?"* Generally, influence had a strong impact on the various metrics. Starting with Shannon entropy in Figure 7.1, greater influence led to lower entropy suggesting that influence creates clearer consensus patterns, such as fewer larger clusters. Influence also had an impact on local receptiveness with higher influence associated with greater local receptiveness (Figure 7.2). This may be a result of influence causing people to become more open to differing opinions. Finally, higher levels of influence were associated more frequently with medium sized opinion clusters and no small clusters. The lack of small clusters indicates that influential individuals may also foster more connections as part of attempts to create consensus. k

Figure 7.2

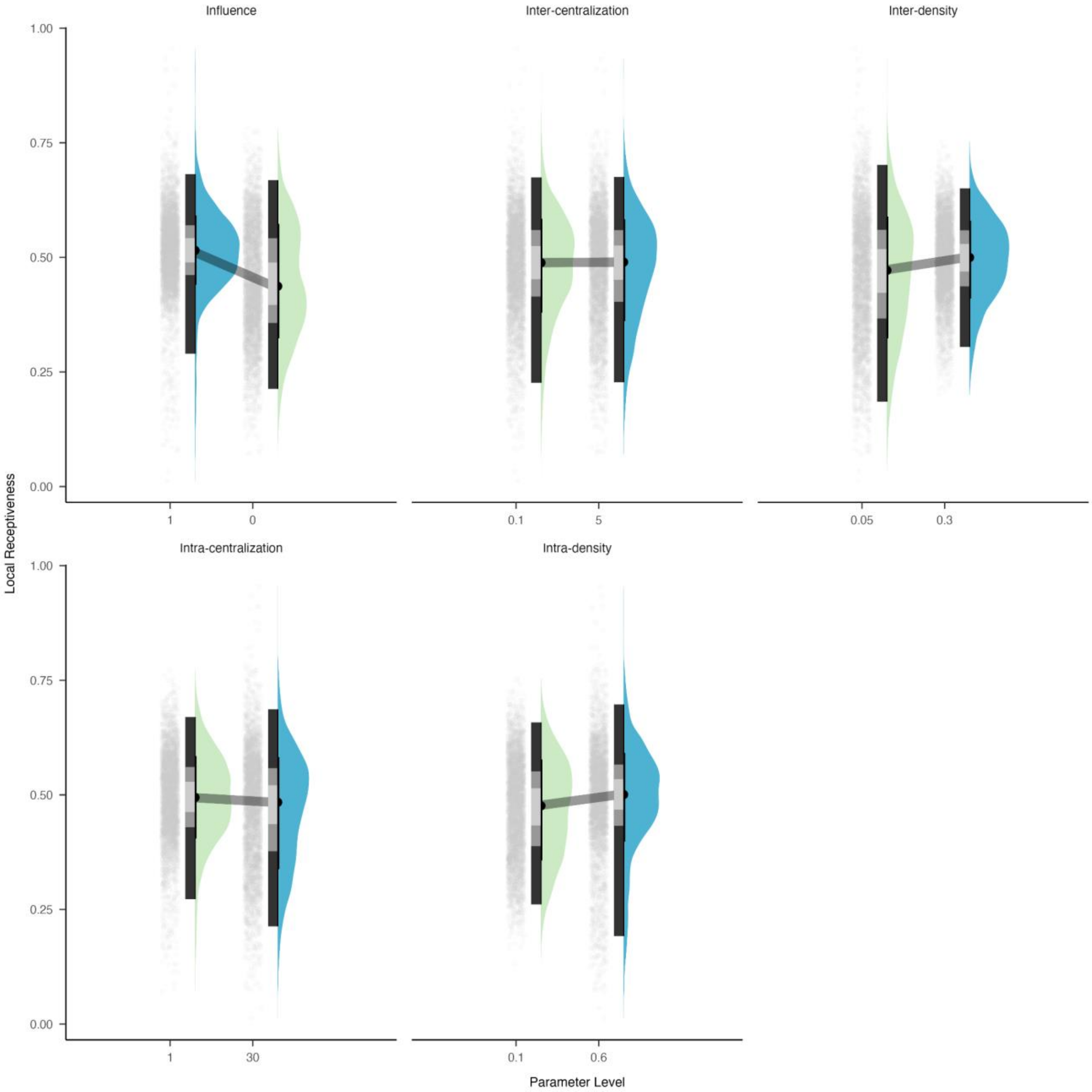
The Effect Of Experimental Variables On Shannon Entropy



Note: the grey points show the output of individual model runs, while the distributions reflect the density of model outputs. The bars show the 50%, 80%, and 95% HDI. The black line spanning between conditions emphasizes the size of the difference between the two median values

Figure 7.3

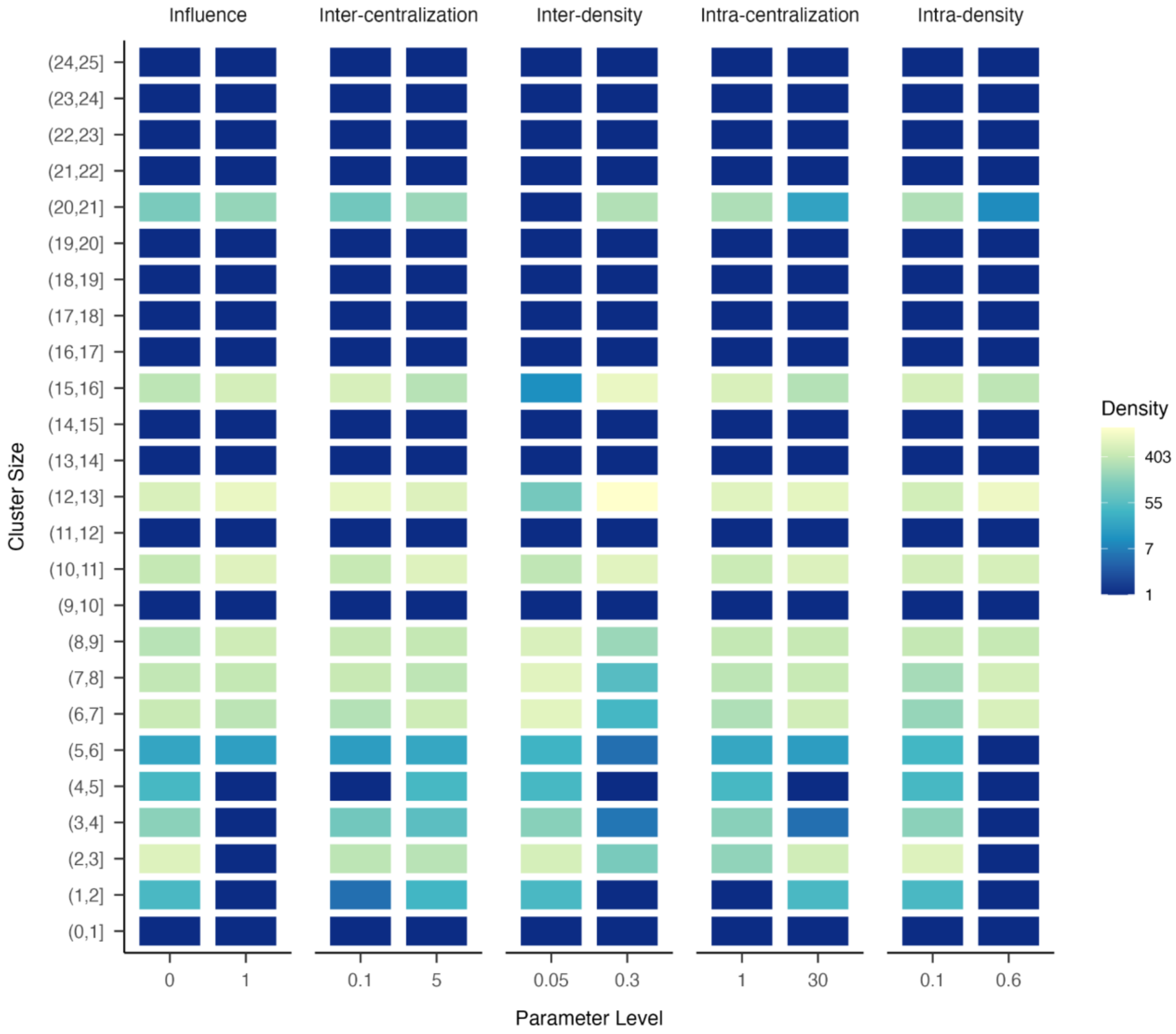
The Effect Of Experimental Variables On Local Receptiveness



Note: the grey points show the output of individual model runs, while the distributions reflect the density of model outputs. The bars show the 50%, 80%, and 95% HDI. The black line spanning between conditions emphasizes the size of the difference between the two median values.

Figure 7.4

The Effect Of Experimental Variables On The Number Of Opinion Clusters



Note: Each tile's color represents the frequency of a particular cluster size occurring within a condition within each factor. Lighter colors represent higher densities.

CHAPTER 8

DISCUSSION

The organizational landscape is extremely competitive, requiring that organizations create objectives that align with current demand, and execute strategies effectively to achieve them. While conceptually what is required is clear, achieving it is challenging. Organizational leaders who are members of different groups, with different perspectives, and individual characteristics, need to align their perspectives regarding strategy to work cooperatively towards success.

While the importance of coming to consensus on strategy has been known for some time, research has primarily investigated the various antecedents of consensus. Such scholarship has identified a variety of predictors of consensus, leading to an expansive nomological network on the subject. Yet, identifying factors that are related to consensus does not help to explain the process through which consensus emerges. Doing so requires that actual mechanisms are specified and systematically tested to determine their ability to explain observed patterns of strategic consensus. As such, the purpose of this dissertation was to initiate the development of a processual theory of strategic consensus through the development, validation, and experimental manipulation of a multilevel, multitheoretical process model. Through this procedure, I was able to develop a robust computational model that is capable of extensive virtual experimentation. Further, evidence was gathered proving the ability of the model to conduct virtual experiments. Specifically, I was able to answer my two initial research questions related to foundational arguments supporting the proposed theory which were: *What* *is the impact of initial communication network structures (i.e., communication centralization and density within and across component groups) of emergent patterns of strategic priority perceptions?* and, *what impact do influential individuals have on eventual patterns of strategic priority perceptions?* **Contributions**

This dissertation provides several important contributions. First, I was able to build and validate a model of strategic consensus. This is an important contribution given the status of scholarship on strategic consensus. Mainly, research has focused on input-process-output models investigating predictors of consensus one variable at a time. This paper, however, investigates the actual process that drives the formation of consensus by integrating multiple theoretical perspectives from multiple levels of analysis into a computational model that can be used going forward to study consensus formation.

A second contribution of this dissertation is that I was able to demonstrate the utility of this model for developing practical interventions for improving consensus in organizations. Indeed, through virtual experimentation I found several intriguing results. For example, I found that with regard to networks of strategy formulation conversations high degrees of within-group communication density, intra-group decentralization, SLS decentralization, and social influence processes may all influence the patterns of strategic opinion perceptions that emerge in organizations.

Third, as a result of the development of this model, I created a "virtual laboratory" that can be used going forward for the in-depth investigation of strategic consensus within SLS. For example, the model was constructed in such a way that it can continue to learn based on newly collected data and can be applied to answer novel research questions. Some of these questions include: what characteristics of SLS or processes lead to faster consensus formation? What are the consequences of different patterns of strategic consensus? Where does strategic consensus originate within the SLS? All these questions may be answered with this model.

Practical implications

This dissertation developed not only an empirical device, but a practical tool as well. Using this model, new and interesting questions can be answered that help to develop interventions that can foster consensus in organizations. For example, training programs, ways to rearrange organizational structures to best nurture consensus, or leadership interventions can all be developed. Perhaps most importantly, beyond conventional interventions, this model allows for specific and unique advice because experiments can be run with the unique characteristics of any organization. Through continued model development the areas through which this model may make an impact may only continue to grow.

Limitations

Although the present study provides important insights, it is important to consider the results within the context of several limitations. First, many potentially relevant individual differences and relational processes were reduced to proxies to focus primarily on the research questions. Future research should expand upon individual differences that are related to processes like homophily, leadership, and informal influence that are foundational to social power, communication, and network structures. Some potentially relevant individual differences may include personality, gender, age, and experience. Similarly, at the dyadic-level, task interdependencies could be formalized to examine the role of task flow in the emergence of consensus.

There are also some potential methodological limitations. For example, the model was based on a limited amount of empirical data. Sample size is important in model development as the data is used to determine appropriate parameter values and assess model validity. When a small sample is used there is the risk of overfitting, or creating a model that is formed to the unique characteristics of the data used, therefore limiting generalizability. However, obtaining data from SLS is notoriously difficult and is one of the primary reasons why strategic consensus research has stagnated. Further, most computational models do not incorporate any empirical data whatsoever and are therefore purely theoretical exercises. As such, the fact that data were able to be incorporated in any capacity is a significant advancement. Moreover, the Bayesian framework used allowed for uncertainty in parameter estimates to be incorporated into the model. Doing so ensured that the observed values were not given undue influence over the results. It is also important to note that the data that was available was limited temporally. There was limited information that could be used to validate the development of consensus over time in detail. Further research and or validation efforts may benefit from collecting intensive longitudinal data on strategic consensus to provide additional support for the theoretical model.

An additional limitation is that only positive effects were incorporated into the model. Indeed, it is theoretically possible that some of the parameters have a negative influence on consensus (e.g., Lungeanu et al., 2022). Additional research should investigate this possibility. The methods used for calibration may also be subject to limitations. For example, the ABC rejection sampling method used for this dissertation requires immense sample sizes. Despite collecting over 70,000 simulated data points, some scholars suggest samples over 100,000, even up to 1,000,000 points depending on model complexity. As such, this method is often deemed impractical due to the computational cost, and the skills required to perform such research. However, ABC calibration also provides much more detailed information than other methods and is therefore a worthy pursuit. Moreover, techniques were used to minimize the impact of sample size, such as incorporating neural networks and using VARS to assess model-based uncertainty. Even so, there are several other feasible methods for estimating parameter values including genetic algorithms that identify point estimates, and Monte-Carlo Markov chain methods of ABC. An interesting extension would be to examine the sensitivity of the results to calibration method and sample size. Finally, the model was only compared against one simplified model. It is possible that there are other more parsimonious processes that were not evaluated. Future research should compare the model against other models incrementally to determine the minimum sufficient model complexity and remove unnecessary parameters.

Conclusion

Through the creation of a verbal theory, I was able to develop and validate a computational model of strategic consensus within the SLS. Doing so allowed for some of the potential processes driving the formation of strategic consensus to finally be clarified, signaling a step forward for our understanding of strategic consensus. The current model serves as the foundation for critical future research as well as impactful practical implications.

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APPENDIX A: SOFTWARE PACKAGES

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