Using Agent-Based Modeling to Test and Integrate Process-Oriented Perspectives of Leadership Emergence

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ABSTRACT

As organizations utilize less hierarchical forms of leadership, the study of how leadership emerges within teams continues to grow in importance. Despite many theoretical perspectives used to study leadership emergence, little is understood about the actual process by which a collective structure emerges. In the current work, I address two of the primary limitations within this literature: imprecise theoretical perspectives and methodological challenges in studying emergence. Specifically, although there are many conceptual works that describe the leadership emergence process, these descriptions do not have enough precision to be able to design a model with formal rules, a necessary requirement for studying emergence. Additionally, studying leadership emergence requires the study of newly formed teams frequently over time, which is challenging to accomplish using existing methods. To address the two above limitations, in the current work, I translate two dominant process-oriented perspectives of leadership emergence (social interactionist and social cognitive) into formal theories that include a series of testable hypotheses. In doing so, these theories outline the essential elements and process mechanisms of each theoretical perspective. Next, I use these theories to design two agent-based models to simulate the process by which leadership emerges within teams, under each perspective. Using the software NetLogo, I simulate 500 newly formed teams over the initial period of 500 dyadic interactions (i.e., hours). Finally, after simulating these models, I use the resulting data to test the predictions from each theoretical perspective. In addition to testing the hypotheses from each model, I also utilize agent-based modeling to systematically test the relative importance of the

unique individual-level elements and process mechanisms from each model. From this entire process, I generate results about (1) how well the agent-based models represent the respective perspectives, and (2) the relative influence each perspective's unique elements and mechanisms have on team outcomes. Overall, results generally supported the core concepts from each perspective, but also identified areas where each perspective needs to revisit for theory on leadership emergence to advance. Specifically, the results illustrated that certain individual-level elements were most influential for leadership emergence. For the social interactionist perspective, it was the comparison between implicit leadership theories and self-prototypical leadership characteristics. For the social cognitive perspective, it was leader self-schemas. Additionally, results indicated that future work may need to revisit the conceptualization of both leadership structure schemas, as well as the dynamic process of weighting implicit leadership theories. Finally, predictions about the rate of leadership emergence over time within the social cognitive perspective were the only predictions that were not supported. From these results, I present multiple themes as a conceptual road map for the advancement of leadership emergence theory. I argue that the lack of support regarding leadership emergence trajectories presents opportunities for a reconceptualization of emergence at the event level, as well as new modeling procedures to capture emergence as it occurs. I also present future study ideas that can directly test the competing assumptions from each perspective. In total, I argue that this work advances the study of leadership emergence by adopting a method that helped integrate two dominant perspectives of leadership emergence, possibly laying the groundwork for the development of a combined formal theory.

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GENERAL AUDIENCE ABSTRACT

The purpose of this dissertation was to understand how specific individuals in teams become viewed as leader, when there is no formal hierarchy. This represents the process of leadership emergence. Most research studying leadership in teams focuses on who becomes a leader. As a result, little is known about the exact process by which certain individuals emerge as a leader. Fortunately, there are theories that represent potential ideas for how this process occurs. However, these theories are difficult to test, as this type of research requires the study of newly formed teams over time, a great methodological challenge. In my dissertation, I attempt to address this challenge by simulating newly formed teams over time using a form of computer simulation called Agent-Based Modeling (ABM). In using ABM, I aimed to learn how two theoretical perspectives both compare and contrast to one another, in how they both explain the process of leadership emergence. In my primary analysis, I simulated 500 teams, working together over a period of hours. After using this data to test a series of predictions, I found that most predictions were supported across each theoretical perspective. This provided evidence that the simulations represented each theoretical perspective. However, the results also showed that certain parts of each theoretical perspective need more research. In recognizing the weaknesses in each perspective in modeling leadership emergence, I introduce multiple opportunities for theoretical integration, in that ideas from both models can be combined into one. Therefore, the findings from this research lay the groundwork for the development of one single theory for how

leadership emerges in groups. Ultimately, this could help understand how leadership in teams occurs, which can lead to new interventions to improve team leadership and performance.

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Introduction

Over the past few decades, the field of leadership has seen a significant shift in perspective, with a substantial increase in theoretical contributions focused on the relational, process-oriented nature of leadership (DeRue, 2011; DeRue & Ashford, 2010; Uhl-Bien, 2006). This change represents a contrast to the widely held, dominant perspective of leadership as a study of individuals with largely stable characteristics (Dinh & Lord, 2012). This modern conceptualization represents leadership as a system of individuals, each transitioning between leader and follower roles over time (DeRue, 2011; DeRue & Ashford, 2010). Of course, these views are not new, as various scholars have discussed these ideas since the origination of leadership studies (e.g., Borgatta, Bales, & Couch, 1953; Barlund, 1962). However, as organizations continue to shift to less hierarchical governance, many have labeled this form of leadership as one of the most critical areas in the future of leadership research (Dinh et al., 2014; Lord, 2017).

This change in the study of leadership is highlighted by the rise in the study of *leadership emergence*, which represents the bottom-up process by which a stable leadership structure forms within a collective of individuals (Lord & Maher, 1990; Schneider & Goktepe, 1983; Taggar, Hackew, & Saha, 1999). In this view, leadership is not a formal role that one individual fills. Instead, this area of research represents leadership as the process by which others view specific individuals as a leader, independent of formal designation. More recently, this research area has adopted the perspective such that all individuals within a collective may fill the role of both leader and follower at various times during which the team completes a task (Denis, Langley, Sergi, 2012; DeRue, 2011; DeRue & Ashford, 2010).

In recent decades, the study of leadership emergence has made some critical advancements. There is now a large and robust literature on what individual factors predict who will emerge as a leader within a team (Emery, Calvard, & Pierce, 2013; Judge, Bono, Ilies, & Gerhardt, 2002; Lord, De Vader, & Alliger, 1986). Additionally, there is a growing literature on the relationship between shared leadership and both team and organizational outcomes (Carson, Tesluk, & Marrone, 2007; Pearce & Sims, 2002). In conjunction, these works address two critical questions about leadership as an informal, collective phenomenon.

Studying leadership emergence through the characteristics of individuals and its impact on relevant outcomes is essential. However, it neglects two necessary pieces of information used to understand an emergent phenomenon. First, according to complexity theory, the phenomenon of emergence is multilevel, given that a novel, macro-level entity emerges from the micro-level elements (Corning, 2002; Goldstein, 1999; Manson, 2001). Therefore, theories of emergence must delineate parts of a phenomenon at the level (individual, dyadic, collective) at which they occur. Second, emergent phenomena are formed not merely through the individual elements they consist of, but instead through the dynamic interactional processes among these micro-level elements (Fromm, 2004; Kozlowski & Klein, 2000). These processes are best represented as the rules that determine *how* the individual-level elements interact with one another over time (Bonabeau, 2002). The study of leadership emergence has progressed by studying the elements of emergence. However, future work is needed that incorporates levels beyond the individual. Additionally, these works need to incorporate the interactional rules which generate a collective phenomenon (Acton, Foti, Lord, Gladfelter, 2019). Without these two pieces of information, the full process of leadership emergence cannot be studied.

Recent works have adopted a more process-oriented perspective to begin to understand the critical mechanisms that connect the micro-level to the macro-level (i.e., meso-level) in an emergent phenomenon. Although largely conceptual, these works begin to fill in the missing gaps in the study of leadership emergence. This growing literature represents ideas from various perspectives, each making different theoretical assumptions, as well as different elements and mechanisms to explain the system-level dynamics of leadership emergence. As such, although these theories have targeted the critical yet elusive process-oriented nature of leadership emergence, they contribute to the problem of theory proliferation. Recent work has identified leadership as an area replete with many theories that describe the same phenomena, yet do not seek to assimilate with one another (Meuser et al., 2016). To address this, many have argued for: (1) frameworks that integrate theoretical perspectives and (2) methods that compare how similar perspectives may better explain observed phenomena (Dinh et al., 2014). In doing so, separate theoretical perspectives can be integrated into a single coherent theory that best represents the leadership phenomenon of interest (Muthukrishna & Henrich, 2019). In integrating the most dominant perspectives that address the underlying processes of leadership emergence, a significant advancement can be made in the study of this critical leadership phenomenon.

Many have argued that agent-based modeling represents the ideal solution to the above challenges (Harrison, Lin, Carroll, & Carley, 2007; Fioretti, 2013; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2016; Weinhardt & Vancouver, 2012). As a form of data simulation designed to understand multilevel, emergent systems, agent-based modeling (ABM) can specifically uncover the critical meso-level processes, which drive leadership emergence. ABM offers three essential benefits for the study of leadership emergence. First, ABM allows the researcher to simulate a social system by inputting both the individual-level elements and interaction rules

used to assess how a collective outcome is formed (Bonabeau, 2002). As such, ABM is both multilevel and process-oriented—the two essential pieces missing from current leadership emergence research (Acton et al., 2019). Second, ABM allows for the systematic assessment of the critical elements and process mechanisms within an emergent system. In doing so, the researcher can test predictions made by respective theories that are difficult to test due to the methodological challenges of collecting intensive longitudinal data (Kozlowski et al., 2016). Finally, by relying on tools such as sensitivity analysis, ABM allows the researcher to empirically evaluate the relative importance of components from various theoretical perspectives in driving the collective outcome (Richiardi, Leombruni, Saam, & Sonnessa, 2006). As such, this can aid in the development an integrative theory that includes only the most critical components from each perspective. Taken together, these benefits of ABM provide the foundation for substantial advancement in the study of leadership emergence.

The purpose of the current work is to utilize both process-oriented theoretical perspectives and agent-based modeling to formally model and test the complete process of leadership emergence in teams. This work is broken down into three parts. First, after elucidating the general literature on process-oriented theories used to described leadership emergence, I outline two dominant perspectives used to model the process of leadership emergence: (1) Social Interactionist perspective and (2) Social Cognitive perspective. In doing so, I translate these theoretical perspectives into formal theories, each with a series of testable hypotheses that are implied within that perspective. Second, I then build two separate agent-based models before testing the predictions made within each theoretical perspective. Third, as these two perspectives are used to describe the same underlying process of leadership emergence, I use sensitivity analysis to test the relative influence of each perspective's models unique constructs.

Specifically, for the unique individual-level constructs, I create a single agent-based model that begins with the shared components across all perspectives before adding in the unique individual-level construct of each perspective into two separate models. In doing so, each unique component is evaluated based on the amount of variance it accounts for in the collective leadership[1] outcomes. Additionally, by comparing the unique leader-follower interactional rules from each perspective's model to a base model, I assess the influence that each interactional rule has on change in leadership outcomes over time.

Ultimately, this three-stage process can make two primary contributions. First, the predictions of each perspective are formally tested using ABM. This test provides an initial evaluation of the relative utility of each separate perspective in explaining leadership emergence. Second, by evaluating the relative influence of each perspective's unique constructs and interactional rules using sensitivity analysis, this can help identify areas of each perspective that may not accurately reflect the leadership emergence process. In doing so, this sensitivity analysis can aid in the development of an integrative theory of leadership emergence that incorporates the most critical components of these various perspectives into a single comprehensive model. This type of work therefore addresses a central tenet of both computational models, as well as the study of emergent phenomena: creating models that use limited rules to predict complex phenomena (Epstein, 2006). In generating both contributions, I advance the study of leadership emergence by integrating existing perspectives into an empirically derived, systematic understanding of the full process of how leadership emerges within teams.

[1] In this paper, I use the term "collective leadership" in reference to the type of leadership that exists at the group level (Contractor et al., 2012). I use the term "shared leadership" to indicate a *particular form* of collective leadership, in that roles are shared across team members. In the current paper, these terms are not interchangeable.

Leadership as an Informal Team Process

Origins of process research. Before covering leadership emergence specifically, it is important to understand the origins of leadership process research. This literature ultimately informs the development of more recent process-oriented perspectives of leadership emergence. Some of the earliest scholars studying leadership and general power dynamics readily acknowledged that the most critical aspects of leadership were not specific leader characteristics (e.g., personality), but the relational dynamics between leaders and followers. For example, in his classic text on social behavior, Homans (1961) argued that the most effective forms of leadership were a result of collaborative exchanges between both leaders and followers, not merely because of a single leader's personality characteristics. In his early work studying teams without formal leaders, Bass (1949) observed that team members would fluctuate between leader and follower roles until the ideal structure was formed. In studying informal discussion teams, Back (1948) observed that teams would demonstrate substantial fluctuations in participation depending on the stage and the team task and that these fluctuations were derived mainly from the sudden rise of particular individuals to the role of leader within the team (independent of any position or label). Bales (1947) also found that in observing small team interactions, teams developed critical patterns of behaviors, which largely determined the team hierarchical structure and leadership dynamics that formed over time.

All these past works share essential commonalities concerning the study of leadership emergence. First, in reporting their findings, they all refer to the idea that, in teams with no formal hierarchy, a stable leadership structure tends to emerge over time. Second, in studying the interaction patterns, these works illustrate that both leadership and followership are flexible roles that individuals fluctuate between, not stable positions. Murphy (1941) summarizes these ideas

eloquently by stating “It is discovered that leadership takes protean forms, that it is unstable, that the qualities necessary at one time are unnecessary at other times, that leaders rise and fall as situations change, that the same individual alternates between leading and following” (p. 674). Overall, the ideas from these classic works culminate to represent leadership as a dynamic team process, rather than a dispositional characteristic (Dinh & Lord, 2012).

Unfortunately, although these early works provide an excellent foundation for studying leadership in teams as a dynamic process, there is limited discussion of the critical process mechanisms that generate the emergence of a collective leadership structure. In this sense, leadership research has neglected the actual process of emergence. To illustrate this, I now introduce multilevel theory of emergent phenomena, before outlining how leadership process research has fit within this epistemological framework.

Multilevel Theory of Emergent Phenomena

The concept of emergence is a direct result of the study of complexity among multilevel systems (Mitchell, 2009). Most phenomena within our universe are complex at some level, which indicates that they are formed by a series of subcomponents that interact over time (Holland, 2000; Mitchell, 2009; Simon, 1991). For example, the human brain functions because billions of neurons communicate with one another over time to create collective neuronal firing patterns, which ultimately produce cognition. Additionally, thousands of ants, which individually can perform only simple behaviors, can collectively perform complex tasks, such as creating large tunnel formations for travel and gathering and sharing necessary resources (Lenoir, Fresneau, Errard, & Hefetz, 1999). Although all of these types of collective systems differ in important ways, they share a critical feature: individual subcomponents self-organize into a unique collective property that forms adaptive functions (Mitchell, 2009). In doing so, they all

represent the concept of emergence, the bottom-up process of self-organization, which ultimately creates a collective phenomenon (Bonabeau, 2002). Although the literature on emergence spans multiple disciplines, most emergent phenomena are made up of three components: (1) the elements of the collective phenomena which serve as its lower-level properties, (2) the dynamic process mechanisms that transfer these micro-components to the collective phenomenon, and (3) the emergent collective property which cannot be reduced to the individual micro-components (Bonabeau, Dessalles, & Grumbach, 1995; Kozlowski & Klein, 2000; Levin, 2005). Not only does each emergent property have these three parts, but each property also is unique from one another based on these three components (Mitchell, 2009). Consequently, if a phenomenon is understood to be an emergent property, these three components of emergence must be included within both the theories and methodologies used to study it.

Recently, Acton and colleagues (2019) reviewed the leadership emergence literature to assess the extent to which these three properties of emergence were discussed. In doing so, they found that the literature predominantly studied the elements of leadership emergence but neglected the underlying process-mechanisms and the dynamics of the collective outcome. Ultimately, they concluded that little advancement had been made in studying leadership emergence because of the lack of understanding about the underlying process mechanisms, which inform leadership emergence (Acton et al., 2019). This conclusion coincides directly with reviews of groups and teams research (Cronin, Weingart, & Todorova, 2011; Kozlowski, 2015). Although current research within teams and leadership discusses the importance of adopting a bottom-up approach to studying collective phenomena, these works remain focused on the individual elements that make up the collectives, which limits the potential advancement in understanding any emergent phenomena.

Challenges in studying processes of emergence. As past works on leadership emergence have neglected the underlying process mechanisms of this emergent phenomenon, it is necessary to ask why this lack of understanding exists. In reviewing past works (Acton et al., 2019; Cronin et al., 2011), two primary reasons for the neglect of the underlying processes of leadership emergence become evident. The first of these two reasons is conceptual, and the second is methodological.

First, historically, some leadership research *has* acknowledged that relational processes form the basis of leadership. One of the noteworthy findings in the Acton et al. (2019) review was that although research on informal leadership has focused on the lower-level elements, some of the earliest works on leadership specifically discuss the underlying processes of leadership emergence. However, although these works do acknowledge a dynamic process, the emergent process is discussed statically. This finding aligns with an important distinction outlined in the teams literature that labeling a phenomenon as a process cannot be equated with adopting a process-oriented perspective (Kozlowski, 2015; Kozlowski, Chao, Grand, Braun, Kuljanin, 2013). To study the actual process of emergence, lower-level elements of a system must be paired with the interaction rules to describe how the collective outcome is generated. This idea is outlined clearly using the modern conceptualization of emergence, initially referred to as "soft emergence" (Bedau, 1997). Under this approach, emergence is best represented as a recipe, where the necessary ingredients are the lower-level elements, and the directions are the rules by which these properties interact with one another.

Current theories on leadership and teams do not align with this modern approach to emergence. Theories may discuss the underlying processes that drive the collective outcome, but they do not do so with enough specificity that it could be formally tested (i.e., rules or

mathematical functions; Vancouver & Weinhardt, 2012). This example is analogous to a recipe where there are no specific measurements. Second, even in the case where a process-oriented theory is at a required level of specificity, these theories rarely include both the elements as well as the process mechanisms in the same theory (Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016; Kozlowski et al., 2014). This example is analogous to a recipe with the cooking directions but no ingredients. To simulate an emergent property, a theory must fulfill both requirements, and research on leadership and teams has failed to do this thus far (Acton et al., 2019; Cronin et al., 2011; Kozlowski et al., 2016).

Even if theories align with the requirements for studying an emergent phenomenon, there remains an empirical challenge that limits advancement in understanding. Studying emergence is unique from studying other phenomena because, to be fully understood, the phenomena must be studied before a collective property forms (Kozlowski, 2015). This concept is reflected by the common adage within the literature that an emergent phenomenon must be grown to be studied (Railsback & Grimm, 2019). Therefore, to study leadership, teams must be studied at inception, and then followed until the stable collective property has emerged. Of course, achieving this is immensely difficult. Studying teams over time is already challenging, but studying them intensively starting at inception, is almost impossible (Bell, Fisher, Brown, & Mann, 2018). This challenge is a crucial reason for limited advancement within the study of emergence in teams (Cronin et al., 2011). As a result, scholars have advocated for the adoption of new theories and methodologies to overcome these significant challenges for studying emergent phenomena (Kozlowski, 2015; Kozlowski et al., 2014).

Aims of current theoretical framework. The objectives of this current work align closely with these two primary challenges in studying emergent phenomena. First, I outline the two

primary process-oriented perspectives that I use to simulate leadership emergence. In elucidating each perspective, I translate theoretical concepts to a formal theory (i.e., formal rules) that addresses the previously discussed requirements for studying emergence. Each theory: (1) includes both the essential elements and process mechanisms of the system, and (2) discusses the process precisely enough to build a simulation that can test predictions. Second, I utilize ABM, which allows for the empirical testing of emergent systems from initial formation over time, using computer simulation. Not only can complex systems be "grown," but the elements and processes can be systematically tested to understand their effect on the collective form that emerges. ABM can thus overcome the many methodological challenges required to study a phenomenon such as leadership emergence.

Perspectives of Leadership Emergence

The leadership literature has failed to develop a complete process-oriented theory of leadership emergence. However, a selection of past works from two areas have introduced ideas that help uncover what the process might be. These two areas continue to have critical influence on the field's understanding of leadership as an informal team process: Social-interactionist perspective (DeRue, 2011; DeRue & Ashford, 2010), and Social Cognitive perspective (Lord, Epitropaki, Foti, & Hansbrough, 2019; Lord, Gatti, & Chiu, 2016). Together, they are identified as the two dominant perspectives that outline the process of leadership emergence, as well as address the limitations of the earlier perspectives. These two perspectives set the foundation for the two sets of hypotheses that I test using agent-based modeling.

Primary theoretical perspectives. In their recent review of the leadership emergence literature, Acton and colleagues (2019) identified the dominant perspectives that seek to describe the leadership emergence process. Of note were two dominant streams of research, which invoke

different philosophical traditions, and make different theoretical assumptions. These two streams represent what I label as the two primary theoretical perspectives of leadership emergence. Although recent articles often adopt combinations of each perspective (e.g., Carnabuci, Emery, Brinberg, 2018; Cook, Meyer, Gockel, & Zill, 2019), both of them incorporate different theoretical assumptions about how the emergence process unfolds. As such, I now outline the conceptualization of the leadership emergence process from these two perspectives: Social Interactionist perspective and Social-Cognitive perspective. In explicating each of these perspectives, I do so in close alignment with complexity theory. To do so requires that each perspective be discussed at a micro-level of detail in a bottom-up fashion (i.e., starting at the individual level). According to multilevel theory of emergent phenomena, an essential property to emergent systems is distinctiveness. Distinctiveness represents the idea that levels can only be discerned from one another because of their unique structures (Mitchell, 2009; Simon, 1991). If the structures were identical, then there would not be separate levels in the system.

Furthermore, as these collective structures are informed by the associated processes that occur at that level, theorists have argued that the processes in a multilevel system are unique at each level (Mitchell, 2009; Simon, 1991). Within the teams literature, Cronin and colleagues (2011) echo this. They state that even in the most homogeneous forms of multilevel systems, the lower levels may be similar in form and function to the higher level, but not identical. As past leadership research has discerned unique elements and processes at the individual, relational, and collective levels of analysis, each of these perspectives is outlined separately at each level.

Each perspective's predictions and leadership outcomes. When outlining how each theoretical perspective describes the leadership emergence process, I specifically note the elements and processes that are unique to each perspective. I then cover the proposed

implications that these elements and processes have on the collective outcomes of leadership emergence. In doing so, I make separate hypotheses for each theoretical perspective regarding its impact on the collective outcome of leadership emergence. The primary outcome of leadership emergence is the collective leadership structure. Researchers have represented this outcome in two ways: the distribution of leadership roles (DeRue, Nahrgang, & Ashford, 2015; Kalish & Luria, 2016), and the time it takes for emergence to develop (Barnlund, 1962; Small & Rentsch, 2011).

These two outcomes are essential not only because they have been discussed in the leadership literature, but also because they reflect the two essential representations of any emergent property: process and level (Kozlowski, 2015; Kozlowski et al., 2013). As emergence is a bottom-up process whereby individual properties develop into a collective outcome, leadership takes time to emerge. As such, to capture the process of emergence, the pace at which the collective outcome emerges (i.e. trajectory). As the collective outcome is emerging, it is critical to capture what the form of the emergent property is (i.e. structure). Since these two pieces of information require one another, they are both necessary to represent emergence. As such, hypotheses in the current work either predict the form of leadership (e.g., shared) or predict the time it takes for a collective leadership structure to emerge. Finally, each perspective theorizes that leadership emergence is represented by both external changes (i.e. leadership ranking), and internal changes (i.e. leader identity; DeRue & Ashford, 2010; Lord et al., 2016). As such, each perspective also incorporates hypotheses about leader and follower identity. I now describe the leadership emergence framework for each of the two primary theoretical perspectives**.**

Social Interactionist Perspective of Leadership

Of the current dominant perspectives that are used to represent the process of leadership emergence, most recent works adopt the social interactionist perspective (SIP) of leadership (Aime, 2014; DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009; DeRue, 2011; DeRue, Nahrgang, Ashford, 2015; Marchiondo, Myers, & Kopelman, 2015; Sullivan, Lungeanu, DeChurch, & Contractor, 2015). The concept of social interactionism originates from sociology, mainly from the philosophies Blumer (1980), Goffman (1959), and others (e.g., Stryker, 2008). This perspective represents an amalgamation of various concepts, all of which center on the idea of meaning being *constructed from* social interaction (Shalin, 1986). That is, how individuals think about and understand their social world is seen to be continuously revised during each subsequent social interaction. Within the study of leadership, a large collection of works has since utilized this perspective in representing how leadership develops within teams.

Applied to the study of leadership, the SIP has a few essential ideas that serve as the foundational pieces of this perspective. First is the idea that identity (or self-concept) is central to the leadership emergence process (DeRue, Ashford, Cotton, 2009). Second is the notion that identity is not a stable entity of the person. Instead, individuals negotiate their identities through behaviors, which serve as symbols for both leadership and followership (DeRue & Ashford, 2010). This idea refers to the fundamental concept of social construction, which states that people actively construct their conception of both themselves and others through social interactions (Bartel & Dutton, 2001). Last is the premise that collective leadership forms through patterns of leader-follower interactions (DeRue, 2011). As these three concepts represent the foundation of this perspective, I now elaborate on them to lay the groundwork for a formal theory of leadership emergence. I use the term formal theory consistent with Sutton and Staw's (1995) description of theory. A formal theory does not just describe phenomena; it addresses its

underlying processes, discusses time scales, and can be formulated into testable hypotheses (Sutton & Staw, 1995). As theoretical perspectives (i.e., narrative theories) do not achieve these goals (Vancouver, Tamanini, & Yoder, 2010), I translate them into formal theories. These formal theories can then generate an agent-based model.

Leadership Identity Construction

The SIP utilizes identity as the central representation of leadership emergence within teams. Thus, to understand how this theoretical perspective represents the emergence process, it is critical first to understand identity in its full complexity. Identity is a challenging topic to study as multiple disciplines each have shaped its history with differing assumptions (Schwartz, Luyckx, & Vignoles, 2011; Wetherell, 2009). Nevertheless, identity represents how people make meaning of their world. Thus, fundamentally, identity is used to shape the past, present, and future into a coherent narrative (Ibarra & Barbulescu, 2010).

Identity is inherently tied to self-concept, but its relationship remains a topic under discussion (Schwartz et al., 2011). Most scholars would argue that the self-concept represents the macro representation of the self, with micro-level identities representing self-representations in domains, including leadership (Markus & Kunda, 1986; Markus & Wurf, 1987; McConnell, 2011). As such, scholars would argue that leadership represents an identity nested within the overall self-concept (Epitropaki, Kark, Mainemelis, & Lord, 2017). Under this perspective, leadership identity is referred to as an ambiguous identity. Leadership is ambiguous because it changes both in definition and meaning across contexts and people (DeRue et al., 2009). For example, adolescent boys might want to be a leader within their sports team but think it is terrible to lead others at school (Ayman & Korabik, 2010). Accordingly, within this perspective, the fundamental idea is that a person develops a unique leader identity *within each social*

context.

Because of leadership being an ambiguous identity, the SIP argues that individuals construct the meaning of leadership through an inherently social process of dynamic negotiation. It is constructed through behavioral "claims and grants," which occur at the dyadic level (DeRue et al., 2009). Claims represent individuals declaring to others that leadership should be a part of their identity; granting represents other people confirming that declaration. Everyone's leader identity is constructed based on these repeated claims and grants (DeRue & Ashford, 2010). Therefore, this identity is not evident initially but is *created through* interactions with others (DeRue & Ashford, 2010). Furthermore, this perspective particularly characterizes the identity construction process as multilevel. Individuals enact their leadership identity (individual level) as a function of their interactions (dyadic level), and this identity becomes stable over time as it is validated from the team (DeRue, 2011).

Although the leadership identity construction process is inherently multilevel, a patterning of leader-follower interactions (DeRue, 2011) captures this process. These interactions, borrowed from the work of Weick (1995) and others, represent the most critical mechanism of the identity construction process. Originally referred to as "double interacts" (Hollander & Willis, 1967), within the team context, they vary in magnitude, dispersion (DeRue, 2011), and temporal patterning (Sullivan et al., 2015). Magnitude refers to how many of these actions are performed across team members, and dispersion refers to who is performing the interacts. The collective leadership structure will change as a function of these aspects of the double interacts. Often overlooked, time will also have an impact as individuals will have memories of previous leader-follower interactions. These memories create a temporal dependence, leading to stable patterns of leader-follower interactions, which is evidence that leadership has emerged to a

collective property (DeRue, 2011). Taken together, although people start with a unique expectation for leadership, they develop a contextualized leader identity through interaction. Finally, through a process of dyadic negotiation, these leader identities will emerge from the individual level to the collective level over time, forming a collective leadership property (DeRue & Ashford, 2010).

Primary Components of Process Model Using SIP

To test the implications that this perspective has for the emergence of leadership within teams, I now elucidate its elements and processes. I start at the individual level, followed by the relational level, finishing with the collective level. Throughout the development of the process-oriented description of this perspective, I define its predictions, which will later be tested using virtual experimentation (Kozlowski et al., 2016). Each prediction will be defined at the level at which it applies within the overall system (e.g., individual).

Individual-level. At the individual level, the SIP emphasizes two critical elements as driving leadership emergence: leadership structure schemas (LSS), and implicit leadership theories (ILT). Both components represent elements or unique variables that everyone within a collective brings to the team (DeRue & Ashford, 2010).

Leadership structure schemas. Leadership structure schemas represent everyone's conceptualization of leadership as either shared (i.e., distributed), or hierarchical. According to DeRue and Ashford (2010), people will decide to engage in leadership/followership based on whether they conceptualize leadership as being either of these two styles. That is, those that view leadership as shared are willing to accept the idea of multiple people performing leadership roles (shared LSS; DeRue & Ashford, 2010). In contrast, people with a hierarchical LSS conceive leadership as being performed by one person.

Under this conceptualization, individuals are unlikely to grant leadership once they have already claimed leadership themselves (Wellman, Ashford, DeRue, Sanchez-Burks, 2014). Extending these ideas further, this LSS should have a direct impact on the extent that person is viewed by others as a leader. Specifically, at the individual level, if individuals with hierarchical LSS begin to enact a leader identity, they will *only reinforce their own leader identity*. As they conceptualize leadership as one directional, they will not reinforce any other leadership claims. Opposingly individuals with a shared LSS will continue other reinforce others leader identities, even after they have claimed leadership. As a result, across interactions, individuals with a hierarchical LSS are more likely to strengthen their own leader identities, during which they are not reinforcing others. As these contextualized identities then drive leadership ratings over time (DeRue & Ashford, 2010), we can predict that individuals with a hierarchical LSS will receive higher leadership ratings than those with a shared LSS.

Hypothesis 1A: If an individual has a hierarchical LSS, then that person will be perceived more as a leader.

As a result of its effect on granting behavior, LSS should also influence the extent to which individuals adopt follower roles. Specifically, as individuals with a shared LSS conceptualized leadership as a plural form, they should be more willing to adopt follower roles across interactions (DeRue & Ashford, 2010). Therefore, within a team, if a person has a shared LSS, they are expected to perform more of a follower role than those with a hierarchical LSS.

*Hypothesis 1B: If an individual has a **s**hared LSS, then that person will perform more of a follower role than people with a hierarchical LSS.*

Regarding the impact of LSS on the collective leadership structure of the team, SIP is not as clear. SIP argues that a team of people all with hierarchical LSS will reach convergence

around one leader, and a team of people all with shared LSS will reach convergence around multiple leaders. However, SIP does not identify the expected structure when there is specific variability in LSS (DeRue and Ashford, 2010). However, when focusing on the elements at the individual level, the distribution of LSS should influence the distribution of leadership roles in the team. As individuals with a shared LSS are more willing to grant leadership to others, teams with more of these people should have a more distributed structure (i.e., more people performing as leaders).

Hypothesis 1C: If teams have a greater proportion of individuals with shared leadership structure schemas, then the team will have more shared leadership structure.

Implicit leadership theories. The concept of implicit leadership theories (ILT) represents each person's individualized representation of leadership. Specifically, among individual-level characteristics (e.g., intelligence, dominance), each person has expectations for the characteristics that another person needs to be a leader (Epitropaki & Martin, 2005). According to the SIP, ILT are expected to have a definite impact at the individual level, via a process of ILT-to-self comparison (DeRue et al., 2009). Initially, after the collective forms, people will first decide to enact a leadership role as a function of the congruence between their attributes and their ILT. The smaller the difference between the ILT and self attributes, the more likely that people will initially claim leadership (DeRue et al., 2009). At the individual level, ILT thus will impact the resulting collective leadership structure. Specifically, across all individuals, the smaller the difference in the ILT-to-self comparison, the more likely it is that individuals will claim leadership. Across the team, average smaller differences should therefore result in more individuals participating in leadership. Ergo, smaller differences should result in a more shared leadership structure.

Hypothesis 1D: If teams have smaller average differences in individual-level, ILT-to-self comparisons, they will have a shared leadership structure.

Dyadic level. As previously mentioned, although individual characteristics are the essential elements of the leadership emergence process, leadership is viewed to emerge through the interactions occurring at the dyadic level (DeRue & Ashford, 2010). Therefore, in any dynamic model of leadership emergence, the fundamental process should be represented as a series of dyadic interactions (DeRue, 2011). Claiming and granting represents the foundation of the leadership construction process (DeRue et al., 2009; Marchiondo et al., 2015). Within each dyadic interaction, whether people claim and grant leadership ultimately reinforces a leader or follower identity (DeRue et al., 2009; DeRue & Ashford, 2010). Although works in this perspective discuss multiple factors that might impact claims and grants, the elements remain the same as the individual level: LSS and ILT (DeRue & Ashford, 2010; DeRue et al., 2015; Wellman et al., 2014).

Leadership structure schemas. As LSS directly influence how individuals behave in dyadic interactions (i.e. granting leadership), its impact at the dyadic level of analysis is reflected by Hypothesis 1C. Specifically, individuals with a shared LSS will perceive dyadic interactions to include more possibilities (L/F, F/L, L/L, F/F), whereas those with a hierarchical LSS perceive two possibilities (L/F, F/L). As a result, having more individuals with a shared LSS will result in more possibilities of both leading and following, resulting in more shared leadership.

Implicit leadership theories. At the dyadic level, if Person A enacts a claim, then Person B will evaluate Person A's characteristics relative to her ILT. If there is congruence between the characteristics and her ILT, Person B is expected to grant leadership (DeRue & Ashford, 2010). Therefore, at the dyadic stage, ILT transition from being compared with self attributes to the

attributes of others (DeRue et al., 2009). This transition should have an important implication for the collective structure of leadership. In particular, the within-dyad variability in ILT-to-other comparisons should drive the extent to which leadership functions are distributed across team members. Specifically, the less variability in these comparisons *within dyads,* the more shared the leadership structure will be.

Hypothesis 1E: If teams have smaller differences in ILT-other comparisons within dyads, then they will have a more shared leadership structure.

Contextualized leader/follower identity. As the individual double interacts between two people are the ultimate building block to leadership emergence, each interaction is viewed in isolation from each other one (DeRue, 2011). However, these interactions are connected over time through a person's development of a coherent leadership identity (DeRue et al., 2009; DeRue & Ashford, 2010). Accordingly, a critical point of this theoretical perspective is that, as dyadic interactions occur over time, two new variables are formed: contextualized leader and follower identities (DeRue et al., 2009; DeRue & Ashford, 2010). According to the SIP, individuals shift from using ILT-to-self comparisons to using only their contextualized leader identity to determine their leader-follower interactions (DeRue & Ashford, 2010). Thus, at this point in team development, individuals will rely on their formed leader identity to determine whether they will claim leadership in the later interaction.

The SIP readily acknowledges that individuals can develop both a leader and a follower identity (DeRue & Ashford, 2010; DeRue, 2011). However, because individuals use ILT-self-comparisons first to determine whether they will claim leadership, they will only think about followership as a function of how their dyadic interactions develop (Carsten, Uhl-Bien, West, Patera, McGregor, 2010; Hollander, 1992). Over time, based on the outcome of each leader-

follower interaction, individuals will begin to develop both leader and follower identities as separate entities (DeRue & Ashford, 2010). For example, if a person has repeatedly granted leadership to others, then over time, that person will internalize a follower identity (DeRue & Ashford, 2010).

Over time, as a result of the dyadic interactions, individuals begin to demonstrate greater consistency in their claims and grants. This consistency is driven from this perspective's assertion that the leader/identity construction process is cyclical (DeRue, 2011). Instead of using ILT to guide interactions, people only use their leader and follower identities. Then, through the subsequent dyadic interactions, each identity is adjusted to align with the actions of others. For example, even if a woman does not have a leader identity, if others continue to grant leadership to her, she can then form a leadership identity (i.e. through experiments to claim leadership; DeRue & Ashford, 2010). As a result of this process, each person should settle into a leader identity that fits the other team members' identities. Over time, this identity will be reinforced by the others within the team (i.e., as it aligns with expectations). Consequently, across time, each person's contextualized leader and follower identities are expected to become more stable, as a function of each dyadic interaction.

Hypothesis 1F: Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.

Hypothesis 1G: Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.

Collective level. As previously discussed, any formal theory of emergent phenomena must acknowledge the collective outcome (Kozlowski, 2015). Most often, this represents changes in the collective outcome over time. As the SIP is represented primarily as a dyadic process, the

collective level is discussed as a pattern of leading and following interactions (DeRue, 2011). Additionally, the collective level is primarily discussed in terms of the idea of collective endorsement, which is the collectively held reputation regarding leadership ability of one individual (DeRue & Ashford, 2010). However, the idea of reputation is discussed as a natural occurrence of the identity construction process (DeRue & Ashford, 2010). As such, a new variable should not be included at the collective level.

Social Cognitive Perspective of Leadership

Rather than leadership being viewed as a personal characteristic or behavior, the social cognitive perspective (SCP) represents leadership as a perception of the follower. This view aligns with most modern perspectives of leadership emergence, including social interactionism. However, SCP goes beyond similar perspectives by focusing on intra-individual mechanisms, which drive the emergence process (Lord et al., 2016). The most notable of these is the concept that people categorize others as a leader using an ILT, but categorize themselves as a leader and follower, using separate leader and follower self-schemas (Lord & Brown, 2003; Lord, Gatti, & Chiu, 2016).

As leadership research has shifted to studying less hierarchical forms of leadership, this perspective has shifted. It now actively incorporates both the multilevel and dynamic aspects of emergent leadership (Lord, et al., 2016). In doing so, SCP perspective has increased its reliance on two ideas: the importance of self-schemas, (Lord, Gatti, & Chiu, 2016) and the dynamic weighting of ILT based on team interaction (Lord & Dinh, 2014). I now expand on these two fundamental concepts.

Multilevel and Dynamic Social Cognition

Historically, SCP aligned closely with social cognitive psychology by incorporating

schemas for both the self and others (e.g., Markus, 1977). Accordingly, just as individuals are viewed to have a cognitive schema for leadership in others, they are also expected to have one for themselves (Epitropaki et al., 2017). When discussing formal leaders, cognitive schemas for others is most critical (Dinh et al., 2014). However, when discussing leadership emergence, self-schemas become particularly critical. Past work has shown that although individuals use cognitive frameworks to organize information about others, they do not use the same frameworks to organize information about themselves (Markus & Wurf, 1987). Research shows that we tend to exhibit biases about ourselves that do not exist when categorizing others (Kwang & Swann, 2010).

Under this updated conceptualization, the process of leadership is driven not only by the self but also by a dynamic negotiation of leader and follower roles. As leadership and followership represent unique social roles, they are reflected by unique self-structures (Epitropaki et al., 2017). The SCP reflects this by describing the leadership emergence process as a function of both leader and follower self-schemas. Therefore, compared to SIP, this perspective does not assume that only ILT drive both individuals' perceptions of others' leadership qualities, as well as themselves. In this perspective, it is just as critical whether individuals associate themselves with a leadership role as they do a followership role. Furthermore, these two self-structures are expected to interact in meaningful ways, with patterns of leader-follower self-schemas making up the driving force, along with ILT and leader-follower interactions.

A second concept that defines the application of the SCP to leadership emergence is the idea that the leadership categorization process is dynamic (Lord et al., 2016; Shondrick & Lord, 2010). Under the more contemporary version of the SCP, leadership perceptions are driven by connectionist networks that continually update based on external information (Dinh & Lord,

2014; Shondrick & Lord, 2010). Individuals initially rely on chronic cognitive representations for leadership through their implicit leadership theories (i.e., ILT). However, over time, they differentially weigh their ILT based on what they observe in the team (Shondrick & Lord, 2010). This process represents the primary mechanisms by which individuals adjust their leadership expectations to others within the team. As a result of this, the structure of leadership among team members should become non-linear, represented through what is referred to as compilational emergence (Kozlowski & Klein, 2000).

These two components represent how the SCP was adapted to multilevel and dynamic contexts fundamental to modeling the leadership emergence process. Based on these ideas, I now elaborate on SCP by outlining the specific mechanisms that would be included in a formal model of leadership emergence.

Primary Components of Process Model Using SCP

Similar to the previous section, I now explicate the elements and process mechanisms that are outlined in the SCP. During this description, I define the predictions across the three primary levels adopted previously.

Individual-level. As the SCP represents a dynamic intra-individual perspective, it can complement other interactional perspectives (e.g., SCP) by modeling the critical within-person changes that drive social interaction. At the individual level, it is represented by two elements: leader and follower self-schemas. For SCP, as implicit leadership theories (ILT) are used for categorizing others, not the self, ILT are best described starting at the dyadic level (Acton et al., 2019).

Leader and follower self-schemas. Compared to SIP, SCP outlines the critical role of the self in determining leader role adoption. Classic work by Markus and colleagues has found that

individuals often have unique cognitive frameworks used to organize information about themselves in different domains (Cross & Markus, 1994; Markus, 1977; Markus & Wurf, 1987). Research has illustrated that people understand followership to be unique from leadership (Uhl-Bien, Riggio, Lowe, & Carsten, 2014). These are not opposite ends of one spectrum, but instead two separate spectrums.

At a basic level, self-schema captures how much a person associates their self-view with a leader and follower role within similar contexts (Cross & Markus, 1994; Markus, 1977). Therefore, leader and follower self-schemas are theorized to be primarily based on past experiences as a leader within that general context. For example, a follower self-schema would be influenced by how often a person tended to adopt follower roles in past groups. As such, how schematic a person is on both leader and follower self-schemas is determined by their past experiences in these roles (Cross & Markus, 1994). A schematic person would easily view themselves as a leader or a follower. Thus, the more leader/follower-schematic a person is, the more likely they are expected the perform a leader/follower role (Epitropaki et al., 2017). Furthermore, as self-schemas are based primarily on past experiences, individuals are expected to begin their experiences in a new team with a separate self-structure for both leader and follower self-schema (Acton et al., 2019).

As individuals will have a self-structure for both leadership and followership, to understand how leader-follower interactions will happen, a pattern approach is required (Epitropaki et al., 2017). That is, a person's specific leader self-schema must be considered within the context of their follower self-schema. A follower's self-schema involves people's reaction to the leadership behavior of others. Therefore, leader/follower self-schemas will have an impact on whether a person decides to enact a leadership role, as well as whether they support

others' attempts to enact that role.

The concept of leader/follower self-schema implies that individuals expect whether they will enact both leader and follower roles before dyadic interactions. At the individual level, proponents of the SCP would argue that the difference between leader and follower self-schema is most critical in determining whether individuals perform a leadership role initially (Epitropaki et al., 2017). Additionally, the importance of self-schemas also implies that individuals do not base their enactment of leadership on their characteristics (e.g., intelligence, dominance) as one would with an ILT. Instead, individuals who are more schematic with the concept of leadership compared to followership will be more likely to enact a leadership role early on. According to complexity theory, the initial micro-interactions within a system are often most critical as they are reinforced continuously within a self-reinforcing collective system (Lichtenstein et al., 2006). Consequently, as self-schemas will drive these early interactions, individuals that are more schematic on leadership than followership would be expected to be more likely to emerge as a leader.

Hypothesis 2A: If an individual is more schematic on leadership than followership, then that individual will be seen more as a leader.

In considering how individual leadership and followership self-schemas might impact the collective team leadership structure, it is crucial to consider the different possible combinations within one individual. According to this perspective, both contextualized leader and follower identities must be formed for a collective leadership structure to emerge (Lord et al., 2016). These contextualized identities require an individual to enact both leader and follower roles (Acton et al., 2019). At the individual level, this perspective argues that individuals have unique cognitive schemas for both leadership and followership before interaction. This idea is essential

to team outcomes because a collective leadership structure requires a team that has both individuals who are schematic on leadership and those who are schematic on followership. Consequently, if all individuals want to be followers but not leaders (follower schematic), or vice-versa (leader schematic), a collective structure will not emerge. Therefore, the more schematic individuals are across both leadership and followership, the more individuals will be participating in leadership. This should result in a more shared leadership structure.

Hypothesis 2B: If teams have individuals who are more schematic on leadership and followership, then they will have a more shared leadership structure.

Dyadic level. Similar to SIP, SCP outlines ILT congruence as the primary mechanism which drives whether each person will perceive the other as a leader (Shondrick, Dinh, Lord, 2010). Furthermore, similarly to SIP, SCP structures the emergence process as a series of dyadic interactions (double interacts). Therefore, at this stage in the emergence process, the structure of any formal model across these perspectives will be similar. However, the SCP remains distinct in its description of the dyadic level of leadership emergence, starting with its representation of ILT.

Implicit leadership theories. At a basic level, ILT are represented similarly across both SCP and SIP. They represent a critical mechanism at the dyadic level through congruence. Across each dyadic interaction, individuals will compare the attributes of a person to their ILT. The more congruent the attributes are to their ILT, the more likely they will adopt a follower identity and grant leadership. However, multilevel concepts from SCP (Epitropaki, Sy, Martin, Tram-Quon, & Topakas, 2013) can extend this view, by theorizing how dyadic congruence *across* dyads should influence leadership structure. Specifically, if some dyads are closely congruent in ILT-other comparisons, but other dyads are not congruent, this should manifest to

unequal distribution of new leadership connections. Consequently, teams with less variability in these ILT-other comparisons across dyads should have a more shared leadership structure.

Hypothesis 2C: If teams have individuals with less variability in ILT-other comparisons across dyads, then they will have a more shared leadership structure.

Although other perspectives note the role of ILT, they are historically discussed in static fashion, as a disposition of the individual (Shondrick, Dinh, Lord, 2010). Within the social cognitive perspective, Dinh and Lord's (2012) describe an updated conceptualization of ILT as dynamic. In integrating complexity theory with SCP, they argue that, at the interactional level, the relative weighting of each person's ILT will change. In particular, not only do individuals directly participate in dyadic interactions, they observe other interactions occurring within the collective. This idea should have a significant impact on the time it takes for a collective leadership structure to emerge. Individuals are expected to adapt their ILT based on the interactions of others within the team. Since each person originally bases these interactions on their ILT, leadership emerges as a function of individuals adapting their ILT to one another. Once a collective leadership property emerges, individuals will have adjusted their original ILT to one that best fits the collective (Acton et al., 2019). As this will occur over a series of interactions, collectives that start with ILT most similar to one another would be expected to have a collective leadership structure emerge the quickest.

Hypothesis 2D: If teams have a smaller difference in ILT across individuals, then they will more quickly reach a collective leadership structure.

Leader and follower self-schemas. The SCP is also distinct from other perspectives in its conceptualization of the continued role of leader and follower self-schemas. Whether someone activates a leader or follower identity is a function of ILT congruence, as well as their self-

schema (Lord, Brown, Freiberg, 1999). Regarding self-schemas, at the dyadic level, the critical mechanism is the congruence between a person's leader self-schema and another person's follower self-schema. Within the SCP perspective, a person will not develop a contextualized leader identity if someone enacting a follower role does not support their leadership claim (DeRue, 2011). This concept is essential because a person that has a weak follower self-schema is unlikely to support any leadership claims, independent of other factors (Epitropaki et al., 2017). Consequently, leadership ties will not form unless there is congruence within a dyad regarding one person's leadership schema and the other person's follower schema. Thus, teams that have smaller differences in these dyadic comparisons should reach a collective structure more quickly.

Hypothesis 2E: If teams have smaller differences in leader self-schema/follower self-schema comparisons within dyads, then they will more quickly reach a collective leadership structure.

Contextualized leader/follower identity. At the dyadic level, the SCP is unique from the SIP because individuals rely on separate self-schemas for leadership. However, both perspectives argue that individuals develop a contextualized leader/follower identity (Epitropaki et al., 2017). According to the SCP, individuals transition from reliance on their self-schema to these two contextualized identities. The two identities thus emerge over time at the dyadic level and are continually updated from each interaction. The SCP is also unique in its incorporation of the ILT at this point in the emergence process. At this stage, individuals begin to contextualize their ILT by adjusting it based on the other dyadic interactions they observe (Acton et al., 2019). As such, over time, individuals ILT are expected to become more similar to one another. This concept is critical because the ILT remains the critical driver for both the contextualized leader/follower

identities. Therefore, although the SIP and SCP describe different mechanisms, both would predict that an individual's contextualized leader/follower identities will become more stable over time.

Hypothesis 2F: Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.

Hypothesis 2G: Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.

Collective level. At the collective level, the process of individual's adjusting their ILT to one another should continue to have a significant impact on the leadership structure over time. Across the entire team, if individuals with specific characteristics tended to emerge as a leader, people would adjust their ILT to align with this person's characteristics. This process represents a critical aspect of any emergent system. Although the collective structures are created in a bottom-up direction, this emergent structure then biases the lower-level processes in a top-down fashion (Bonabeau, 2002). Furthermore, this represents the potential utility of SCP for describing leadership emergence; it can connect the collective properties of the team to the cognitive changes occurring within each person. Regarding leadership, this would manifest through relative leadership rank more stable, as a result of individuals' using an ILT that is weighted based on previous hierarchy.

Hypothesis 2H: Across time, each individual's leadership rank will become more consistent.

As each of the two perspectives has been introduced and their predictions outlined, I now describe the primary methodology used to assess them: agent-based modeling.

Agent-Based Modeling

Agent-based modeling represents a form of computational modeling. Computational modeling is the process of using computer simulations to build and test mathematical models (Gilbert & Bankes, 2002). Before the creation of computers, mathematical equations were used to represent entire systems (e.g. weather system). As a result, it was difficult to model complex systems using mathematical equations, in that most of these systems included many non-linear components. Non-linear systems are incredibly complex to solve without a computer, and thus mathematicians used other solutions such as linearization to simulate such systems (Eriksson, Estep, Hansbo, & Johnson, 1996). However, with the creation of computer simulations, complex systems could be simulated much more easily. Consequently, the concept of computational models has existed since the origins of computers and has increased in use exponentially since that time (Eriksson et al., 1996).

Historically, most computational models aligned more closely with what is referred to today as equation-based modeling (EBM; Epstein, 2006). Using EBM, an individual system is simulated based on a series of equations, with each one representing an individual part of the system (Parunak, Savit, & Riolo, 1998). An example of an EBM would be a model that simulates one individual's job performance based on a set of variables, including task difficulty and general intelligence. The person designing the model (i.e., modeler) can then manipulate the parameters of the system to assess the impact of each parameter on outcomes. In this sense, the fundamental unit within equation-based models are the individual equations, which make up the overall system (Vancouver, Li, Weinhardt, Steel, 2016). Unless explicitly modeled, the idiosyncrasies across individual units (e.g., persons) are not recognized within a system. As such, although these approaches can be adapted, the general focus is on modeling a system at one level of analysis (Parunak et al., 1998).

ABM represents a form of computational modeling that is designed to incorporate a system that includes multiple levels. Accordingly, these models are well-fitting to the idea of emergent properties because one of the primary goals is to simulate the collective outcomes that develop from a group of agents (i.e., lower-level units; (Bonabeau, 2002). ABM still utilizes mathematical equations similarly to EBM, but the focus is on each agent as well as between-agent interactions, rather than the overall system (Bankes, 2002). As such, while EBMs rely on differential equations, ABMs tend to rely on rules, which govern how individual agents act, as well as how agents work together (Macy & Willer, 2002). By inputting a few basic rules into a multilevel system, the modeler can study how non-linear, emergent properties form over time as agents continue to interact. As such, ABM represents a truly bottom-up approach (Railsback & Grimm, 2019).

At its core, ABMs have three properties: agents, interactions, and system-level properties (environment; Railsback & Grimm, 2019). Within an overall collective system, agents represent the individual level properties. Each agent can potentially contain distinctive properties—referred to here as elements—that make it unique from every other agent in the system (Epstein, 2006). Some examples of agents could be individual neurons within a part of the brain, individual ants within a larger colony, or individual people within a team. Individual agents can be assigned both stable and dynamic characteristics. Additionally, these characteristics can be represented as both assigned values and stochastic values, with any chosen distribution (Railsback & Grimm, 2019).

An important characteristic of ABMs is that agents interact with other agents based on rules (Railsback & Grimm, 2019). Depending on the model parameters, agents can then learn and update their knowledge based upon their interactions with other agents. Accordingly, agent

behavior is most often temporally dependent, in that it is based on each agent's prior learning (Kozlowski et al., 2016). Whereas individual-level characteristics are often treated as stable within research, ABM can directly model the fluctuations that occur in within-person characteristics over time (Wilensky & Rand, 2015). Finally, ABM allows for complete flexibility in how the model is set up (i.e. initial parameters). For example, although it might be challenging to study teams made up of diverse individuals, an ABM can create this level of diversity in the team (Fioretti, 2013; Kozlowski et al., 2016). All of these qualities of ABM are important for studying leadership emergence, as they address many of the core methodological challenges discussed earlier.

Outlining of Model Components and ODD Protocol

As in any area of study, the use of ABM for science has devolved into multiple "camps," with each having different modeling procedures and assumptions. As a result, some have argued that one of the most considerable challenges to ABM research is the lack of standardization among modeling procedures used (Railsback & Grimm, 2019). Lack of standardization makes it difficult to translate and communicate model information to others, one of the core values in science (Grimm, 2020). Due to this challenge, Grimm and colleagues introduced a standard protocol for describing agent-based models, now referred to as the ODD protocol (Grimm, Berger, DeAngelis, & Polhill, 2010). ODD stands for overview, design concepts, and details (Grimm, 2020). ODD has since been used as a dominant approach across many fields, now being used in over 10,000 different agent-based models (Railsback & Grimm, 2019).

I now briefly outline all the components of the ODD framework to increase the reader's understanding of the core pieces of ABM (see Appendix A for summary). For extended coverage of each of these components, see Railsback and Grimm (2019).

Overview. The overview of any ABM concerns the core descriptions required to understand that model. First, this includes a *purpose* outline, which covers why the model is being designed, as well as the main conclusions that are hoped to be derived from the model (Grimm et al., 2010). Next, to verify the usefulness of the model, every collective system should demonstrate patterns in its primary outcomes (Polhill, 2010). If the results of the ABM do not align at all with expected patterns, then this may be an indication that the ABM design is unsuitable for the phenomena of interest (Grimm et al., 2010).

After defining the overall purpose and expected patterns of the model, the next step is defining the entities, state variables, and time scales in the model (Railsback & Grimm, 2019). *Entities* concern individual-level variables that are stable in that the modeler inputs them into the model, and they do not change over each iteration (Railsback & Grimm, 2019). *State* variables represent individual variables that change as a function of the interactions among agents (Grimm et al., 2010). *Time scales* refer to the conceptual representation of time in the model (e.g. each time step represents hours; Grimm et al., 2010).

Finally, the modeler must define the underlying processes and scheduling in the model. The *process overview and scheduling* section answer the question of what happens when the model is initialized (Grimm et al., 2010). Therefore, to address this, the modeler must describe in specific terms what happens step-by-step as the model proceeds (Railsback & Grimm, 2019). In the case of team interaction, this will mean describing how the agents interact with one another over time.

Design concepts. As ABM simulates an emergent system, the modeler should outline which parts of the model are emergent (Grimm et al., 2010). Some aspects of a model may be deterministic in that that the parameters are imposed on the model, and they do not develop in a

bottom-up non-linear fashion (Railsback & Grimm, 2019). The modeler should also define to what extent do the model includes adaptation. That is, are there any rules that allow the agents to learn from other agents and respectively change their future actions based on this learning (Railsback & Grimm, 2019)?

The modeler should describe the *learning* process within the model (Grimm et al., 2010). The modeler should also provide information about the specific form of *interaction* within the model. Finally, the concept of stochasticity is crucial to any ABM. Any stochastic model components will lead to random variation in the collective outcome. If there are no stochastic components, then every model that is run under the same settings (i.e., model parameter values) will lead to an identical outcome (Railsback & Grimm, 2019).

Model details. The final section of the ODD protocol concerns the structural details of the ABM. Primarily, this concerns two components: *Initialization* and *Submodels* (Railsback & Grimm, 2019). *Initialization* refers to the initial setup of the model. This initial setup represents the starting parameters, including the number of agents and initial values for each parameter (Grimm et al., 2010). *Submodels* refer to the idea that the ABM can be broken down into smaller subcomponents or stages (Grimm et al., 2010). Knowing the initial parameters, as well as the subcomponents of the overall model, is required for others to understand the ABM.

Evaluation of ABM models. Essential to any ABM is how it will be evaluated. *Virtual experimentation* represents one of the most common uses of ABM within the sciences (Macy & Miller, 2002). The primary function of ABM is descriptive as it allows for the modeler to continuously change parameters and observe how the outcome changes (Railsback & Grimm, 2019). However, as science involves the systematic testing of theories, ABM allows for the testing of variables systematically selected from a parameter space (Railsback & Grimm, 2019).

As such, when using virtual experimentation, the modeler chooses both the parameter(s) to systematically vary, as well as the parameter values to vary across. Thus, virtual experimentation represents a powerful tool for hypothesis testing. For this reason, I utilize virtual experimentation to test the set of predictions made previously, separately for the two leadership emergence perspectives.

Sensitivity analysis is one of the most used applications of ABM across the sciences (Thiele, Kurth, Grimm, 2014). Sensitivity analysis represents a deductive approach, as certain parameters are tested to assess which elements, processes, and environmental variables are most important to the emergent outcome (Railsback & Grimm, 2019). There are many approaches to sensitivity analysis, but local sensitivity analysis is often recommended first because only one factor within the model (i.e., interactional rule) is changed at a time (Railsback & Grimm, 2019). This analysis can thus directly assess the impact of changing a model parameter of interest (Thiele et al., 2014).

Sensitivity analysis has many applications, but it is particularly powerful for revising existing theories in the pursuit of a core value of computational modeling: parsimony (Railsback & Grimm, 2019). Unnecessarily complex systems will generate theory that is difficult to test or ultimately apply to real-world issues (e.g., improving team dynamics; Kozlowski et al., 2016). As previously noted, this is especially the case within the leadership emergence literature, with many theories describing the same phenomena using different perspectives (Acton et al., 2019). In this case, the recommended application of sensitivity analysis is to build a model that has mostly shared components from across perspectives, and one unique component from each perspective (Grimm et al., 2010). By doing this, the modeler can test the relative influence of the unique components from each perspective. The modeler can then use this information to

understand how the overall theory can be revised (Railsback & Grimm, 2019). Overall, this process can help generate conclusions that can assist in the development of a revised, integrated theory.

Method

Based on the above concepts in the ODD protocol, I now outline the method used in the current work. The method I used is broken into the three sections previously covered: model design, virtual experimentation, and sensitivity analyses.

Model Design

I now describe the methods used to build the two agent-based models in this work. These methods are summarized across each of the sections in the ODD protocol, as well as Tables 1a-d and 2a-d.

Purpose. The purpose of this work was to design and test two agent-based models that represent the process of leadership emergence occurring in newly formed teams separately for two theoretical perspectives: social interactionist and social cognitive. In doing so, the higher-level purpose (Grimm, 2020) of these models is to generate new knowledge about how different elements and process mechanisms across two process-oriented perspectives influence leadership emergence in teams. Within this overall purpose are two specific purposes. The first is to utilize the models to simulate data representing collective leadership over time. In doing so, I can (1) test how well each model reflects the theoretical perspective it represents and (2) have a better understanding of how certain elements and process mechanisms within each perspective influence collective outcomes (Grimm, 2020). The second specific purpose is to systematically manipulate only the elements and interactional rules unique to each perspective, in order to compare their relative utility in explaining leadership emergence (Grimm et al., 2010). All models were built and implemented in the software NetLogo (version 6.1.0; Wilensky, 1999)

To assess the overall validity of the models, I completed a model piloting process, to assess whether the model produced the expected *patterns* (Railsback & Grimm, 2019). Based on

the past literature from both perspectives, I primarily focused on whether the simulations produced two patterns. First, I assessed whether a collective leadership was emerging over time. As will be discussed, this was assessed using a version of an Intraclass correlation formula (ICC(1)) that measured the agreement in leadership ratings towards individuals over time. Second, I assessed whether individuals tended to develop contextualized leader and follower identities over time. I also expected variability in these patterns, in that not all teams should follow the same trajectories in emergence, and not all agents should develop the same identities (DeRue, 2011).

Entities, state variables, and time scales. Each agent-based model had six agents that represent six people working in a newly formed team. As each perspective is focused on the internal dynamics of leader emergence, the environment is not explicitly included in either model. The individual-level variables (i.e. elements) in the social interactionist model are listed in Table 1a and the individual-level variables (i.e. elements) in the social cognitive model are listed in Table 2a. Both models include two core agent variables: a prototypical ILT (ILTi), and an individual's standing on prototypical leadership traits (Ci). Although implicit theories of leadership include multiple traits, to simply the models, I chose to focus on the traits most associated with leadership roles, referred to as prototypical leadership characteristics (e.g. dominance; Epitropaki & Martin, 2004; 2005). As such, in the simulation, ILT represents one agent's expectation for others regarding prototypical leadership characteristics, and the characteristics represent each agent's actual standing on these traits. These are entity variables in that they are static and inputted into the simulation (Grimm, 2020). Both models also include a contextualized leader identity (LIi) and follower identity (FIi) which represent state variables, as they are constructed from interactions (Grimm, 2020). Finally, each model has a dyadic

variable—representing each agents leadership perception of each other agent. The collective outcomes are discussed in a later section. The unique agent variable from the social interactionist perspective was leadership structure schemas (LSSi), and the unique agent variables from the social cognitive perspective were leader self-schemas (LSSi) and follower self-schemas (FSSi).

At each time step in the simulation, two agents participated in a dyadic interaction, representing an opportunity to both claim and grant leadership. As these dyadic interactions represented actions that each take seconds to a few minutes (e.g. explaining to team members an idea; Marchiondo et al., 2015), I chose a total time scale of 500 interactions. As I aimed to study the initial developmental period of leadership emergence in teams, this would be representative of the initial hours (less than 100) that a new team has spent working together.

Process overview and scheduling. A step-by-step walk through of each simulation (i.e. pseudocode) is presented for the social interactionist model in Table 1b and the social cognitive model in Table 2b. The basic process for both models at each time step occurs as follows. Two agents were randomly selected for a dyadic interaction. A series of smaller steps were then implemented at each interaction. These interactions were separated across two-stages, (1) before all agents had participated in ten interactions, and (2) after all have been involved in ten interactions. During both stages, each agent first decided whether to claim leadership, followed by then deciding to grant leadership. Based on the outcomes of these decisions, each agent updated his or her leader and follower identity, and his or her leadership perception score for the other agent. The difference across the two stages was the information agents used to claim and grant leadership. In the social interactionist model, agents used their follower identity to grant leadership; in the social cognitive model a weighted ILT is used. Finally, all decisions based on

schemas and identities were stochastic, in that an individual's schema or identity only made them more or less likely to enact leadership.

Design concepts. Both agent-based models are intended to be a simplified, yet accurate representation of the leadership emergence process for each theoretical framework. As such, to best provide the full scope of information for each model, I cover the model assumptions that underlie these design concepts. This information is provided in Tables 1c (social interactionist) and 2c (social cognitive). To be clear, these assumptions represent simplifying assumptions, in that they aim to accurately represent narrative theory in using the least rules and elements. This follows the common guideline in model building—to aim for parsimony or what some call the "KISS" principle (Alexrod, 1997; Grand et al, 2016).

Initialization and outcome parameters. To assist in the understanding of the two-primary agent-based models used in this work, I include a list of model variables with starting values in Tables 1d and 2d. An important aspect of building a model is selecting a "sample space" of input parameters that align with past literature. In the case of this work, agents should have characteristics that would possibly be observed in a real person. To address this, I used the previous literature to simulate possible combinations of the core person-level continuous variables in each model. First, for both models, I simulated a series of possible combinations of prototypical implicit leadership theories (ILTi) as well as prototypical leadership characteristics (Ci). To assign agents a combination of values that represents the theoretical parameter space, I simulated these variables based on the work of Epitropaki & Martin (2005). Specifically, for prototypical ILT, I used Epitropaki & Martin's (2005) measure that covers the traits of sensitivity, intelligence, motivation, and dynamism. To represent observed prototypical characteristics, I used their measure of leadership prototype recognition, which represents

participant ratings of the same characteristics in managers. I simulated a distribution of agent variables by using a variance-covariance matrix based on the variable values in their work. This accounted for the observed correlation between these observed ILT dimensions and prototypical values. I chose not to use a self-rating of prototypical ILT values because of the expected inflated correlations between self-ratings and positive traits, based on the work of David Dunning illustrating the inaccuracy of self-perception (Caputo & Dunning, 2005; Dunning, 2012; Dunning, Perie, Story, 1991). Finally, for the social-cognitive model, I simulated patterns of leader and follower self-schema values to represent each agent. As an extension of my previous work, I used the variance and covariances for these two variables observed in a leader and follower self-schema scale that I previously developed (Acton & Foti, 2019). Each measure represents the extent to which individuals associate themselves with leader and follower roles, respectively (See Appendix B for items). In using these input parameters, both models more accurately represented the underlying theoretical perspectives.

This models in this work also had three primary team outcome variables. Two of the variables represent shared leadership: density and centralization. Density represents the overall amount of leadership ties and was calculated by the sum of all dyadic leadership ratings. Centralization represents the extent to which leadership roles are *not distributed* (Butts, 2008). Specifically, in this work, it represents how much leadership tends to be centralized to one person within the team. To calculate centralization, I used a normalized version of Freeman's (1978) general centralization formula:

$$\frac{\sum_{i=1}^{N} Cx(p*) - Cx(pi)}{\max \sum_{i=1}^{N} Cx(p*) - Cx(pi)}$$

This formula represents the sum of differences between the agent with the largest centrality in leadership (i.e. most central; $p*$), and all of the other agents, divided by the

maximum possible sum of differences to normalize the metric. The final outcome I collected was a representation of leadership emergence. Specifically, I used the level of agreement in leadership ratings. This was assessed using an adapted version of the intraclass correlation 1 (*ICC (1)*), which is used as a team agreement statistic (Bliese, 2000); this was calculated for incoming leadership ratings (i.e. ratings towards one agent) and is defined as follows:

$$\frac{Variance\ in\ incoming\ leadership\ ratings\ across\ people\ in\ the\ team}{Variance\ in\ incoming\ leadership\ ratings\ across\ people\ in\ the\ team + \text{Average}\ Variance\ in\ leadership\ ratings\ towards\ people}$$

Summary of models. Based on the above model characteristics, I proceeded forward by performing the simulation across a sample of 500 teams. This sample was chosen based on the recommendations regarding multilevel power analysis (Scherbaum & Ferreter, 2009), as well as the recommended sample size using the program "G*Power" (Faul, Erdfelder, Lang, & Buchner, 2007), assuming small effects, which reflect the assumed effect sizes in the leadership literature (Paterson, Harms, Steel, & Creed, 2016). This sample was chosen so that the statistical tests were well powered, but not so much that null hypothesis significance testing would be uninformative (Lakens & Evers, 2014). Nevertheless, I based my interpretation of results on effect sizes (e.g, Funder & Ozer, 2019).

Virtual Experimentation Method

Tables 1e and 2e summarize the underlying predictions tested using the datasets produced from each of the two models. As the hypotheses test different levels of a multilevel system, they are analyzed with different components of the overall data generated from the simulations. Specifically, I used four versions of the data: person-level data at the last time point, team-level data at the last time point, individual-level data over time, and team-level data over time. For each longitudinal hypothesis, I walk the reader through the recommended growth modeling procedure used (Singer, Willett, & Willett, 2003).

Sensitivity Analysis Methods

As discussed previously, sensitivity analyses allow the modeler to test for the relative importance of model parameters or interactional rules in the emergent collective outcome (Thiele et al., 2014). It also allows for the qualitative and quantitative assessment of whether the inclusion of model parameters or interactional rules improves model fidelity relative to expected patterns or outside empirical data (Yang & Gilbert, 2008). These two uses of sensitivity analysis represent the two objectives for how I use sensitivity analysis in the current work. To achieve these two objectives, I am using two types of sensitivity analysis: (1) one factor at a time (OFAT) and regression based (RB) sensitivity analysis.

One Factor at a Time (OFAT) sensitivity analysis is often the first recommended step for a newly tested model, due to its simplicity and ease of interpretation (Railsback & Grimm, 2019). Specifically, this analysis involves systematically varying the model parameter of interest and holding the other parameters constant. In doing so, the modeler can generate a coherent understanding of the isolated influence of that single model parameter on collective outcomes. This analysis therefore fits closely with the aims of the current paper, to evaluate the unique influence of model elements and interactional rules on outcomes (see Table 3).

OFAT sensitivity analysis is effective at demonstrating the influence of one parameter but does not create a relative metric for comparing different types of parameters *across* models. Alternatively, regression-based (RB) sensitivity analysis can address this limitation by demonstrating how important different model elements are, using common statistical metrics such as R^2. The final step in the sensitivity analyses was thus to use RB sensitivity analysis. The purpose of this analysis was to estimate the relative influence of the core unique elements from each perspective on collective team outcomes. To achieve this, the first step was to build two

basic simulations that only included the core rules from both perspectives. These two simulations were identical other than having the addition of the core individual-level elements from each perspective (leadership structure schemas and leader/follower self-schemas). The models had the same general structure with teams working together across 500 total dyadic interactions. The total sample for each simulation was 500 teams.

Results

The results are separated across two primary sections: (1) hypothesis testing using virtual experimentation and (2) sensitivity analysis. For the hypothesis prediction section, as each framework was tested using distinct models, these results are discussed separately. For the multilevel models performed, I followed past conventions (e.g., Raudenbush & Bryk, 2002; Snijders & Bosker, 2011). This included grand mean centering the focal continuous predictor variables (i.e. independent variable tested) in the respective multilevel models. Additionally, due to the limitations in using restricted maximum likelihood for model comparison, I utilized full maximum likelihood for all multilevel models. Finally, in interpreting effect sizes for the models, I rely on prominent papers across different effect size metrics (Cohen, 1992; Funder & Ozer, 2019; Mathieu, Aguinis, Culpepper, 2012).

Social Interactionist Hypothesis Testing

Individual level. Table 4A displays the means, standard deviations, and correlations for model variables at the individual level, for the final time point. The individual-level data were as follows. The first variable was leadership structure schema and concerns whether a person had a hierarchical or shared leadership structure schema. The second variable was each person's standing on prototypical implicit leadership theory traits, (e.g., intelligence; Epitropaki & Martin, 2004). The third variable represented an individual's prototypical ILT. This variable referred to a person's expectation for how high a leader should be on these prototypical leadership traits. The fourth variable was the within-person, ILT (prototypical) to self-characteristic difference. A smaller difference would mean that a person's characteristics were closer to her expectations for leadership. Leader and follower identity represented each person's identities, which were constructed from her dyadic interactions. As previously described, these represented the extent to

which a person views herself as a leader and follower, within that specific team context. Leader score represented each person's current standing on leadership within the team. Follower score represented a person's current standing as a follower. Thus, the follower score represented a person's average perception of others as a leader.

Across all correlations, patterns overall were representative of what would be expected from the social interactionist perspective. Leadership structure schema (LSS) was not significantly correlated with leader score but was positively correlated with follower score, and this relationship was medium strength (.32, p <.01). This result was expected as, based on the earlier theorizing, those with a Shared LSS were more likely to grant leadership to others. As would be expected, a person's standing on prototypical leadership traits was positively and moderately correlated with her leader score (.33, p <.01). The higher a person was on prototypical leadership traits, the more they were perceived as a leader within the team. This result supports past theory that suggests that individuals higher on these specific traits are more likely to be in leadership roles (Junker & van Dick, 2014). Also expected by theory (DeRue & Ashford, 2010), contextualized leader and follower identities were strongly related to a person's leader (.88, p <.01) and follower score (.83, p <.01), respectively. Finally, leader and follower scores were moderately and positively correlated (.31, p <.01).

Hypothesis 1A. Hypothesis 1A was at the individual level of analysis and concerned a person's leader standing within the team. Specifically, I predicted that individuals with hierarchical leadership structure schemas would be more likely to be perceived as a leader. This hypothesis is multilevel as a person's leadership standing is dependent on the leadership standing of others within the team. As such, this prediction requires multilevel modeling (Raudenbush & Bryk, 2002). Accordingly, to test Hypothesis 1A, I used a form of mixed-effects regression,

which allows the intercept of the relationship between LSS and leader score to vary across teams; this model is often referred to as a random-intercepts model (Snijders & Bosker, 2011). In support of hypothesis 1A, individuals with a hierarchical LSS had significantly higher leader scores (b = .18 t = 4.76, p < .001) within the team. In order to estimate the size of this effect, I calculated the R^2 of the estimated fixed effect of leadership structure schema on leader scores. To interpret the influence, I utilized marginal R^2, representing the influence of the predictor independent of other model components (i.e. random effects). The marginal R^2 was .01. For reference, the conditional R^2 (variance accounted for by both fixed effects and random effects) was .36. Finally, to assess whether including LSS into the model accounts for significance variance, I performed a nested model test; to test for the effect of this predictor above a null multilevel model with no predictor (i.e., unconditional means model; Snijders, & Bosker, 2011). The model that includes LSS led to significantly improved model fit (χ^2 = 22.22, p < .001). Overall, these results show that although there is evidence that having a hierarchical LSS predicts higher perceptions leadership from others, these effects were small.

Hypothesis 1B. Hypothesis 1B was at the individual level of analysis and concerned a person's follower role within the team. Specifically, I predicted that individuals with a shared LSS would be more of a follower. Similar to hypothesis 1A, this hypothesis is also multilevel as a person's follower role is dependent on the other individuals within the team. As such, I again used mixed-effects regression to let the intercept of the relationship between LSS and followership to vary across teams. In support of hypothesis 1B, individuals with a shared LSS had significantly higher follower scores (b = .56, t = 21.92, p < .001). In order to estimate the size of this effect, I calculated the R^2 of the estimated fixed effect of LSS on follower scores. The marginal R^2 was .08, which demonstrates that although significant, these effects are smaller in

size (Cohen, 1992). Finally, I performed a nested model test, which tests for the effect of this predictor above the unconditional means model. The model that includes LSS led to significantly improved model fit ($\chi^2 = 444.13$, $p < .001$). Overall, these results show evidence that having a shared LSS predicts higher followership and these effects were small.

Team level. Table 4B displays the means, standard deviations, and correlations for model variables at the team level, for the final time point. The first three team-level variables report team member attributes. Specifically, the first variable was the average within-person difference in team members' ILT and their standing on these prototypical traits. Larger differences showed that, on average, team members had less congruence between their expectations for leadership and their traits. The second variable was the average difference in ILT and observed prototypical traits *between two people* in a dyad. Larger differences meant that dyads in the team were less congruent in ILT-other comparisons. The next two variables were *ICC (1)* values, representing leader rating agreement (Bliese, 2000); these were calculated for both incoming leadership ties and outgoing leadership ties. Higher incoming leadership agreement was representative of emergence, as the amount of variability in ratings towards individuals was smaller compared to the variability across people (Kozlowski & Klein, 2000). The last two variables represented the two most common measures of shared leadership: density and centralization (Carson, Tesluk, & Marrone, 2007; Small & Rentsch, 2011). Density represents the overall strength of ties in the leadership network, and centralization represents how centralized leadership is to one person (Butts, 2006). As such, shared leadership would be illustrated by higher density and lower centralization (DeRue, 2011).

Across all correlations, patterns were overall representative of what would be expected from the theoretical perspective (Contractor, DeChurch, Carson, Carter, Keegan, 2012; DeRue et

al., 2015). As expected, the average difference between individuals ILT and their characteristics was negatively related to leadership density (-.77, p <.01) and positively related to leadership centralization (.69, p <.01). Additionally, ILT-other difference was also negatively correlated with leadership density (-.60, p <.01) and positively correlated with leadership centralization (.53, p <.01), aligning with expectations. Overall, less congruence between expectations for leadership and observed characteristics was associated with less shared leadership. Supporting past theory (DeRue & Ashford, 2010), the proportion of shared leadership schemas was positively related to leadership density (.30, p <.01) and negatively related to centralization (-.19, p <.01). Following past works in social network analysis (Butts, 2009), leadership centralization and density were strongly negatively related (-.84, p <.01). Finally, agreement in incoming leadership ties was strongly associated with leadership centralization (.79, p <.01) and density (-.64, p <.01), suggesting that an emergent structure was signified by a more centralized form of leadership, a theme I revisit later in the paper.

Hypothesis 1C. Hypothesis 1C was at the team level of analysis, and it concerned the proportion of shared leadership structure schemas in a team and its influence on the teams' leadership structure. I predicted that teams with more individuals with a shared leadership structure schema would have a more shared form of leadership. As the proportion of shared LSS is an ordinal variable, it was entered as the ordinal focal predictor in an OLS regression model. This model estimated the overall effect of the shared LSS predictor and is thus interpreted on the ratio scale. This analysis was performed separately for density and centralization. In support of my prediction, the effect of the proportion of shared LSS was a positive and significant predictor of leadership density (b = 31.89, t = 7.13 p < .001). As a measure of effect size, the adjusted R^2 of the model was .09, and the standardized regression weight was .30. Again, in support of the

hypothesis, the linear effect of the proportion of shared LSS was a negative and significant predictor of leadership centralization (b = -.41 t = -4.34, p < .001). As a measure of effect size, the adjusted R^2 of the model was .03, and the standardized regression weight was -.19. Although the density model demonstrates larger effects, together, both models provide small support for hypothesis 1C. Teams with more individuals that have a Shared LSS tended to have more shared leadership, but the effects were small.

Hypothesis 1D. Hypothesis 1D is similar to 1C because it concerned the leadership structure of the team. I predicted that teams with smaller differences in ILT-self characteristic comparisons (i.e., more within-person congruence) would have a more shared form of leadership. Like hypothesis 1C, this model was performed separately for density and centralization. In support of my prediction, ILT-to-self difference was a negative and significant predictor of leadership density (b = -.92, t = -27.15, p < .001). As a measure of effect size, the adjusted R^2 of the model was .60, and the standardized regression weight was -.77. Again, in support of the hypothesis, ILT-to-self characteristic difference was a positive and significant predictor of leadership centralization (b = .02, t = 21.10, p< .001). As a measure of effect size, the adjusted R^2 of the model was .47, and the standardized regression weight was .69. These were large effects and demonstrated strong support for hypothesis 1D (Cohen, 1992). Teams with, on average, smaller within-person ILT-self characteristic differences (i.e., more congruence between leadership expectations and their characteristics) tended to have more shared leadership.

Hypothesis 1E. Hypothesis 1E also concerned the leadership structure of the team. I predicted that teams with smaller average differences in ILT-to-other comparisons (more within dyad congruence in ILT-characteristic comparisons) would have a more shared form of leadership. As was the case with the previous two models, this model was performed separately

for density and centralization. In support of my prediction, ILT-to-other difference was a negative and significant predictor of leadership density (b = -.79, t = -16.61, p < .001). As a measure of effect size, the adjusted R^2 of the model was .36, and the standardized regression weight was -.60. Again, in support of the hypothesis, ILT-to-other difference was a positive and significant predictor of leadership centralization (b = .01, t = 14.11, p < .001). As a measure of effect size, the adjusted R^2 of the model was .29, and the standardized regression weight was .53. These were moderate-large effects (Cohen, 1992; Chin, 1998) and demonstrated medium-strong support for hypothesis 1E. Teams with, on average, smaller between-person ILT- characteristic differences (i.e., more congruence between expectations for leadership and observed characteristics in others), tended to have a more shared form of leadership.

Over time. The final two hypotheses concerned the change in a person's leader and follower identity over time. I predicted that both identities would become more stable within people over time. First, to assess stability, the model was structured so that identity ranges from 0 (never enacted identity)-100 (always enacted identity); as such, the most *unstable* a person's identity could be was 50. This score represented that a person was equally likely to enact or not enact a leader/follower identity. Enactment specifically referred to the act of claiming leadership within a dyadic interaction. Thus, hypotheses 1F and 1G were tested by how distant a person's leader and follower identities were from 50. I calculated the absolute difference of leader and follower identity from 50 as a measure of leader and follower identity stability.

These final two hypotheses were multilevel because time is nested within each person, and each person is nested within a team. Consequently, to test hypotheses 1F and 1G, I utilized a form of random effects growth modeling that can account for both 2-level (person) and 3-level (team) factors.

Auto-correlation. The data produced from the agent-based simulation was expected to be serially correlated. At each iteration of the simulation, the error term for any variable was equal to its value at the previous time point ± a constant. For example, one person's identity score is = the last iteration's identity score ± a constant (e.g., 1). As such, at each time point, the errors should be almost perfectly correlated with the prior time point. Without modeling this serial correlation, the error structures will be incorrectly modeled, resulting in inaccurate estimates (Dow, Burton, White, & Reitz, 1984). One recommended solution for this scenario is to use an autoregressive model for the errors (Jongerling, Laurenceau, & Hamaker, 2015). Specifically, in a mixed-methods framework, it is recommended to include an additional autocorrelation parameter that accounts for this time dependency in the errors. In the modeling process that I am using, I chose to include the most common version of this parameter, an autoregressive order one (AR(1)) term (Jongerling et al., 2015). This term incorporates the dependency on the error structures from one time point to the previous time point. This model also estimates the phi (Φ) parameter, which indicates how much (0-1) serial correlation exists in the data (Bliese, Maltarich, Hendricks, 2018). Based on these recommendations, I included these procedures into the overall stepwise modeling process.

For both the leader and follower identity hypotheses, I followed the overall recommendations for growth modeling by Singer and colleagues (Singer, et al., 2003). Since not all agents had enough interactions to calculate outcomes shortly after team formation, the dataset started at interaction 75 and continued until the last time point (500). Additionally, as only two agents participated in each interaction, one iteration does not represent meaningful change at the individual level. As such, I used every ten dyadic interactions, representative of one time point.

Accordingly, the number of time points used in the analysis was 43, with each iteration representing ten dyadic interactions.

Before testing the two final predictions, I used this time series data, at the team level, to assess whether it represents a pattern of emergence. Emergence would be represented by an increase in agreement among perceptions within a team (Kozlowski & Klein, 2000). Across all teams, there was a significant increase (b = .00, t =27.82, p< .001) in rating agreement (ICC 1), illustrating that leadership consistently emerged within teams. As theory suggests that leadership emergence is represented by a collective structure and stable identities (DeRue & Ashford, 2010), this result was a prerequisite before testing the final two predictions about identity stability.

Stepwise growth modeling procedure. Model 1 was a growth model with identity stability as the dependent variable, time as the independent variable, with slopes fixed across individuals. Across people, there was significant increase in both leader identity stability (b = .07 p < .001) and follower identity stability (b = .10, p < .001) over time. To account for possible variation in growth trajectories, Model 2 allowed the rate of change in identity stability to vary across people. This model fit the data significantly better than model 1 for both leader identity stability (χ^2 = 273030.12, p < .001) and follower identity stability (χ^2 = 233855.86, p < .001). Overall, individuals demonstrated significant differences in their growth trajectories for leader and follower identity stability. To account for possible nesting at the team level, Model 3 added a team parameter to the random effects portion of the model, which tests for significant differences in identity stability slopes *across* teams. Model 3 fit the data significantly better than model 2 for leader identity stability (χ^2 = 33.12, p <.001) and follower identity stability (χ^2 = 556.56, p <

.001). These results illustrate that there were significant between-team differences in leader identity stability and follower identity stability change.

As such, I proceeded with the three-level model for both leader and follower identity stability. Finally, to account for serial correlation, Model 4 added an autoregressive (1) term to the previous best-fitting model for both leader and follower identity stability. In adding the AR(1) term onto the 3-level model for leader identity, the model failed to reach convergence, suggesting model redundancy (Fox & Monette, 1992). Due to the relatively small effects of using the 3-level model over the 2-level model ($\chi^2 = 33.12$), I included the AR(1) term in a 2-level model. This autoregressive model was better fitting for both leader identity stability ($\chi^2 = 333715.85$, $p < .001$) and follower identity stability ($\chi^2 = 326839.98$, $p < .001$), and the average phi parameters were .99 for both models. As these final models demonstrated the best fit, I proceeded to test both hypotheses 1F and 1G using these models.

Hypothesis 1F. I predicted that over time, the leader identity of individuals would become more stable. Results of the growth model indicated that the fixed effect parameter for time was both positive and significant ($b = .06$, $p < .001$). Using Nakagawa, Johnson and Schielzeth's (2017) marginal R^2 metric for mixed-effects models, the effect size for time was moderate-large, $R^2 = .31$. These results provide strong evidence that leader identity became more stable over time, supporting hypothesis 1F.

Hypothesis 1G. I predicted that over time, the follower identities of individuals would become more stable. Results of the growth model indicated that the fixed effect for time was both positive and significant ($b = .09$, $p < .001$). Using Nakagawa and colleagues (2017) marginal R^2 metric, the effect size of time was large, $R^2 = .50$. These results provide support for a growth effect in follower identity stability over time, supporting hypothesis 1G. Overall,

supporting the social-interactionist theoretical framework (e.g., DeRue, 2011), team members' leader and follower identities grew more stable over time, and this effect was large.

Social Cognitive Hypothesis Testing

Individual level. Table 5A displays the means, standard deviations, and correlations for model variables at the individual level, for the final time point. The first variable was leader self-schema and concerned the extent to which leadership was a part of an individual's self-concept. The second variable was follower self-schema and concerned the extent to which followership was a part of an individual's self-concept. The third variable was each person's standing on prototypical implicit leadership theory traits. The fourth variable represented an individual's prototypical ILT (i.e., leadership expectations for others). The fifth variable was the within-person difference between an individual's prototypical ILT and her standing on these traits. The sixth variable was the average difference between a person's ILT (expectations for others) and the traits of others (prototypical self-traits) in the team. The final four variables were included in the previous framework, specifically, the follower identity, leader identity, leader score, and follower score, for each person.

Most correlations were aligned with what would be expected from the social cognitive perspective. Leader self-schema was significantly correlated with leader identity at moderate strength (.41, p <.01), and follower identity at small strength (.17, $p < .01$). Follower self-schema was significantly correlated with follower identity at moderate-large strength (.52, $p <.01$), and leader identity at small strength (.16, $p < .01$). These results closely align with the expectations of this theoretical perspective. First, it supports that leader/follower identity would be strongly related to leader/follower self-schema, but that substantial variation will also be due to other factors (e.g., ILT; Lord et al., 2016). Second, as past literature illustrates that leader and follower

roles are often shared (Sullivan et al., 2015), leader/follower self-schema should relate to the opposite identity. Leader self-schema had a small but positive relationship with follower identity (.17, $p < .01$). Follower self-schema had a small but positive relationship with leader identity (.16, $p < .01$). Leader self-schema had a moderate positive relationship with leader score (.45, $p < .01$).

Both leader and follower self-schema were uncorrelated with follower score. Although this was inconsistent compared to the leader score correlations, it aligns with the theoretical assumption that granting leadership to others is driven largely by a person's weighted ILT (Acton et al., 2019). Similar to the social interactionist perspective, a person's standing on prototypical leadership traits had a small positive association with leader identity (.23, $p < .01$) and large positive association with leader score (.45, $p < .01$). Despite having different rules compared to the previous perspective, this model also produced strong negative correlations between ILT-self characteristic differences and both leader identity and leader score. The average difference between a person's ILT and the standing of team members on these leadership traits had a small negative correlation with follower score (-.17, $p < .01$), and a very small negative correlation with follower identity (-.08, $p < .05$). This result is interesting as it suggests that these differences have more of an influence on a person's follower role than her follower identity. As expected, leader identity and follower identity had a very strong positive correlation with the leader and follower scores, respectively. The correlation between follower identity and follower score was much smaller (.47 compared to .86 for the leader identity-score relationship). This again reflects the theoretical assumption that ILT, not follower identity, drive the granting of leadership to others. Finally, as a meaningful distinction from the previous perspective, leader and follower scores were not significantly correlated.

Hypothesis 2A. Hypothesis 2A was at the individual level of analysis and concerned a person's leadership standing within the team. I predicted that the more schematic that a person was on leadership compared to followership, the more she would be perceived as a leader. This hypothesis was multilevel as a person's leadership standing is dependent on the leadership standing of others within the team. As such, this prediction requires multilevel modeling (Raudenbush & Bryk, 2002). Accordingly, I used a random-intercepts model (Snijders & Bosker, 2011). In support of hypothesis 2A, the higher the leader self-schema score compared to the follower self-schema score, a person was perceived as a leader (b = .03, t = *17.14*, p< .001). In order to estimate the size of this effect, I calculated the R^2 of the estimated fixed effect. The marginal R^2 was .09, representing small effects (Cohen, 1992). Finally, to assess whether including LSS into the model accounts for significance variance, I performed a nested model test that tests for the effect of this predictor above a null multilevel model with no predictors (i.e., Unconditional means model; Snijders & Bosker, 2011). The model that included leader-follower self-schema difference led to a significantly improved model fit (χ^2 = 280.52, p < .001). Overall, these results show support for the theoretical claim that individuals more schematic on leadership than followership will be more likely to be perceived as a leader, although the effects were small.

Team level. Table 5B displays the means, standard deviations, and correlations for model variables at the team level, for the final time point. The first three team-level variables concerned member attributes. Specifically, the first variable was the team's average *within-dyad* difference in a leader and partner's follower self-schema. This variable represents how similar a person's leader self-schema is to her dyadic partner's follower self-schema. The second variable was the team's variability in ILT-other characteristic difference, *across dyads*. More substantial differences would mean that dyads were more different from one another in their ILT- other

dyadic congruences. The third variable represented the overall variability in prototypical ILT (i.e., expectations for others), across team members. The next two variables were *ICC(1)* values (Bliese, 2000), which define both agreements in leadership ratings *towards a person*, representing emergence, and agreement in ratings *from one person*. Finally, as representations of shared leadership, the last two variables were leadership density and centralization.

Across all correlations, patterns were overall representative of what would be expected from the theoretical perspective (Epitropaki et al., 2017; Lord et al., 2016). As expected, the average within-dyad difference between leader and follower self-schema was negatively related to leadership density (-.09, p <.05) and positively related to leadership centralization (.10, p <.05), although the effects were small. Additionally, the between dyad variability in ILT-other difference had a moderate negative association with leadership density (-.45, p <.01) and a moderate positive association with leadership centralization (.40, p <.01), aligning with expectations. Unexpectedly, variability in ILT across individuals on the team was not significantly related to leadership outcomes. The other team-level variables had similar relationships as the previous perspective.

Hypothesis 2B. Hypothesis 2B was at the team level of analysis and concerned the average team leader and follower self-schemas. I predicted that the more schematic team members were on leadership and followership the more shared leadership there would be. This analysis had two parts, with both leader and follower self-schemas being tested. As such, I performed one linear regression model, with both leader and follower self-schema means as separate predictors. This analysis was performed separately for density and centralization. In support of my prediction, the average leader self-schema was a positive and significant predictor of leadership density ($b = .26, t = 10.48, p < .001$). In performing a *t to r* conversion, the

correlation of this effect was .43, representing very large effects (Funder and Ozer, 2019). Again, in support of the hypothesis, average leader self-schema was a negative and significant predictor of leadership centralization ($b = -.01$ $t = -6.64$, $p < .001$). In performing a *t to r* conversion, the correlation of this effect was -.29, representing medium sized effects (Funder and Ozer, 2019). Average follower self-schema did not significantly predict leadership density ($t = -.01$, $p = .51$) or centralization ($t = .00$, $p = .27$). As a measure of effect size across both predictors, the adjusted R^2 of the density model was .19, and the centralization model was .08. Overall, the results showed support for the role of leader self-schema, but not follower self-schema. Consequently, the overall hypothesis was partially supported, with a strong level of support for the influence of average leader self-schema on shared leadership.

Hypothesis 2C. Hypothesis 2C was also at the team level and concerned the variability in ILT to other person characteristic differences *across dyads.* I predicted that teams with smaller differences across dyads in ILT-other comparisons would have a more shared form of leadership. Similar to hypothesis 1C, this model was performed separately for density and centralization. In support of my prediction, ILT-other team variability was a negative and significant predictor of leadership density ($b = -.05$ $t = -11.24$, $p < .001$). As a measure of effect size, the adjusted R^2 of the model was .20, and the standardized regression weight was -.45. Again, in support of the hypothesis, ILT-other team variability was a positive and significant predictor of leadership centralization ($b = .00$, $t = 9.70$, $p < .001$). As a measure of effect size, the adjusted R^2 of the model was .16, and the standardized regression weight was .40. Although the centralization model demonstrated smaller effects, with the moderate effects in the density model, there was overall small-moderate support for hypothesis 2C. Teams with, on average, smaller across dyad variability in ILT-other differences had more shared leadership.

Over time. The next two hypotheses concerned the rate at which a stable leadership structure emerged. Each of these two predictions regarded the influence of team-level compositional variables on *how quickly* a team reached an emergent leadership structure. This data was multilevel (i.e., time nested within teams), and thus required the use of growth curve modeling. To test both hypotheses, I followed past recommendations in using a stepwise modeling process that increased in complexity at each step (Bliese, et al., 2018). The final step for each hypothesis was to include the focal team predictor (i.e. predictor being tested) in the growth model. Then, to test the hypothesis, I utilized both the fixed effects estimates of interest. Again, I used every ten dyadic interactions, representing a single time point. Since all team members had interactions starting at interaction 75, the number of time points used in the analysis was 43, with each iteration representing ten dyadic interactions.

As stated previously, the data produced from the agent-based simulation was expected to be serially correlated. Based on previous recommendations, I again included these procedures into the overall modeling process. As hypotheses 2d and 2e concerned the rate at which leadership emerges in teams, this would be represented by the slope value for time. To follow modeling guidelines (Singer, Willett, & Willett, 2003), Model 1 was a linear growth model with the slopes fixed across teams. The fixed effects parameter for time was positive and significant (.01, $p < .001$). This result indicated that, on average, teams tended to increase in the agreement of leadership ratings. Therefore, the model illustrated emergence occurring over time. Model 2 was a growth model that allowed the slope parameter for time to vary *across teams* (i.e., random effects). After performing a model comparison test, Model 2 fit the data significantly better than model 1 (χ^2 (1) = 39946.62, $p < .001$), illustrating that there was significant variability in the rate of emergence across teams. Model 3 added an autoregressive (AR(1)) term to account for the

correlated errors across time. This model fits the data significantly better than model 2 (χ^2 = 27905.04, p <.001). Furthermore, the phi parameter was .98. Together, this demonstrated that using an autoregressive mixed-effects model (AR(1)) was appropriate.

Hypothesis 2D & 2E. Models 4a and 4b were designed to test hypotheses 2D and 2E, respectively. Model 4a was identical to Model 3, but included the focal predictor, team prototypical ILT variance, to assess the influence of ILT variability on the rate at which leadership emerged. Following hypothesis 2D, teams that had less ILT variability were expected to have a greater rate of change (i.e., slope) in the agreement of leadership ratings, suggesting quicker emergence. This hypothesis was not supported, as the interaction between time and ILT variance was not significant (b= -.00, p = .34). Hypothesis 2E predicted that teams with smaller differences in leader/follower self-schema comparisons (i.e. more dyadic congruence in self-schema) within dyads would have leadership emerge more quickly. Model 4B tested this hypothesis by adding the average dyadic self-schema difference as a fixed effect, as well as its interaction with time. Hypothesis 2E was not supported, as the interaction between time and dyadic self-schema difference was not significant (b= .00, p = .09). Overall, both predictions regarding the influence of team composition on how quickly leadership emerges were not supported.

Individual identity and role over time. The final three hypotheses in this perspective concerned the change in individual leader/follower identity and leadership standing over time. The first two hypotheses are identical to the final two hypotheses of the social interactionist perspective, as they concerned the stability of identity over time. Specifically, I predicted that team members would increase in stability for both leader and follower identities over time. As the data was multilevel and I expected the data to be affected by serial correlation, I used the

identical growth modeling procedures as the previous perspective. Specifically, I used a mixed model procedure that estimates the overall influence of time (fixed effect) on identity stability, and tests for the effect of both person and team-level variance. Again, I used every ten dyadic interactions, representing a single time point. Since all team members had interactions starting at interaction 75, the number of time points used in the analysis was again 43, with each iteration representing ten dyadic interactions.

Stepwise growth modeling procedure. For both the leader and follower identity hypotheses, model 1 was a growth model with identity stability as the dependent variable, time as the independent variable, with slopes fixed across individuals. Across people, there was significant increase in both leader identity stability ($b = .04$, $p < .001$) and follower identity stability ($b = .06$, $p < .001$) over time. To account for possible variation in growth trajectories, Model 2 allowed the rate of change in identity stability to vary across people. This model fit the data significantly better than model 1 for both leader identity stability ($\chi^2 = 407577.12$, $p < .001$) and follower identity stability ($\chi^2 = 359902.70$, $p < .001$). Overall, individuals demonstrated significant differences in their growth trajectories for leader and follower identity stability. To account for possible nesting at the team level, Model 3 added a team parameter to the random effects portion of the model, which tests for significant differences in identity stability slopes *across* teams. Model 3 did not fit the data significantly better than model 2 for leader identity stability ($\chi^2 = .75$, $p = .86$), but did fit the data better for follower identity stability ($\chi^2 = 282.19$, $p < .001$). These results illustrated that there were *not* significant between-team differences in leader identity stability change, but there were between-team differences in follower identity stability change.

As such, I proceeded forward with the two-level model for leader identity stability and the three-level model for follower identity stability. Finally, to account for serial correlation, Model 4 added an AR(1) term to the previous best-fitting model for both leader and follower identity stability. This autoregressive model was better fitting for both leader identity stability (χ^2 = 312941.48, $p < .001$) and follower identity stability (χ^2 = 294779.95, $p < .001$), and the average phi parameters were .99 for both models. As this final model demonstrated the best fit, I proceeded forward in testing both hypotheses 2F and 2G using these models.

Hypothesis 2F. I predicted that over time, the leader identity of individuals would become more stable. Results of the growth model indicated that the fixed effect for time was both positive and significant (b = .04, $p < .001$). Using Nakagawa and colleagues' (2017) marginal R^2 metric, the effect size for time was small to moderate, R^2 =.14. These results provided support for a growth effect in leader identity stability over time, supporting hypothesis 2F.

Hypothesis 2G. I predicted that over time, the follower identity of individuals would become more stable. Results of the growth model indicated that the fixed effect for time was both positive and significant (b = .06, $p < .001$). Using Nakagawa and colleagues' (2017) marginal R^2 metric, the effect size of time was large, R^2 =.38. These results provide strong support for a growth effect in follower identity stability over time, supporting hypothesis 2G.

Hypothesis 2H. For the final hypothesis, I predicted that over time, an individual's relative leadership ranking in the team would become more stable. For this prediction, I used the time-series data to test the last two hypotheses. Support for this hypothesis would be evidenced by respective time-series correlations (e.g., time-1 rank correlated with time-2 rank) becoming stronger over time. Accordingly, to test this hypothesis, I used four time points, equally spaced

across the team's lifecycle. These were as follows: time 0 (i.e., first time point), time 10, time 20, time 30, and time 40. After selecting these data points, I then calculated the correlations among all combinations. As the data was ordinal, I used the Spearman rank correlation coefficient (Lyerly, 1952). The results are displayed in Table 6. As predicted, the time-series correlation for leadership rank increased over time, with the following values (.73, .88, .92, .94). Next, I tested whether each correlation was significantly different from the previous correlation using a Fisher R-Z transformation (Fisher, 1915). As predicted, the time 2-to-3 correlation was significantly larger than time 1-to-2 ($Z = 17$, $p < .001$), time 3-to-4 was significantly larger than 2-to-3 ($Z = 9.9$ $p < .001$), and time 4-to-5 was significantly larger than time 3-to-4 ($Z = 3.92$, $p = .001$). In total, the results provide strong support Hypothesis 2H; the relative leadership rank of team members became more stable over time.

One Factor at a Time (OFAT) Sensitivity Analyses for Individual Elements

Social Interactionist Perspective

OFAT sensitivity analysis for the role of LSS. To assess the role of leadership structure schemas (LSS) on the team outcomes in this study, first I had to create a dataset that varied across all possible combinations of LSS on the team. As LSS are a categorical variable with two levels (shared or hierarchical), I calculated the permutation of a two-factor variable across a team of six people. This calculation amounted to 64 possible combinations of LSS on the team. Next, I created a dataset with each of these LSS combinations, with all the other individual-level elements in the model held constant. I chose to use the average of these other elements from the previous data, as this constant value. This decision follows recommendations to use data that is supported by past theory and empirical work (Railsback & Grimm, 2019). As this dataset was generated based on parameters from the past literature, the average value reflects what would be

observed in teams. Finally, as the simulations still include multiple stochastic elements, there is variability in the outcomes that is not due to LSS. As such, I performed 15 replications of these 64 team combinations of LSS. The final dataset used for the sensitivity analysis, therefore, had 960 teams. I proceeded to test the role of the *proportion of shared LSS* on the primary outcomes of this study: leadership density, leadership centralization, and leadership rating agreement. Similar to the previous data, agents interacted 500 times. Therefore, the role of the *proportion of shared LSS* was assessed at three distinct time periods, early (at dyadic interaction 100), middle (at dyadic interaction 250), and late (at dyadic interaction 500). For this type of sensitivity analysis, it is recommended to use plots for each variable, to understand its impact on outcomes (Railsback & Grimm, 2019; Richiardi, Leombruni, Saam, & Sonnessa, 2006). I follow these recommendations in plotting the results of the sensitivity analysis and interpreting them descriptively. The results are represented in Figure 1.

Leadership density. At interactions 100 and 250, there was not a clear relationship between the *proportion of LSS* and leadership density. However, at interaction 500, there was a clear positive and linear-shaped relationship between these two variables. Teams that had a greater proportion of individuals with shared LSS, tended to have greater leadership density.

Leadership centralization. At interactions 100 and 250, there was not a clear relationship between the *proportion of LSS* and leadership centralization. However, at interaction 500, there was a clear negative and somewhat linear-shaped relationship between these two variables. Teams that had a greater proportion of individuals with shared LSS, tended to have less leadership centralization.

Leadership rating agreement. At interactions 100 and 250, there is not a clear relationship between the *proportion of LSS* and leadership rating agreement. However, at

interaction 500, there was a clear negative relationship and somewhat linear-shaped relationship between these two variables. Teams that had a greater proportion of individuals with shared LSS, tended to have less leadership rating agreement.

OFAT sensitivity analysis for SIP interactional rule. The social interactionist perspective's central interactional rule is that contextualized leader and follower identities drive dyadic interactions. To assess the influence of this interactional rule, I created two datasets. The first had the same parameters from the model performed to test hypotheses 1A-1G. The second included the identical individual-level element value input parameters but changed the interactional rule so that it continues to use the ILT-other characteristic matching rule. Consequently, any differences in outcomes can be isolated to the contextualized identity interactional rule.

To visualize the influence of the international rule on outcomes over time, I created a time-series graph that plots the average trajectory of each dependent variable across all teams, over time. As discussed earlier, because not all teams had data at the earlier interaction periods, the initial time point in the graph was 75, and the final time point was 500. Finally, each interaction does not represent the full team, as only two individuals actively participated. As such, to represent team changes, I separated time into every ten dyadic interactions, totaling 42 total periods. The results are displayed in Figure 2.

Leadership density. In the first half of the team member interactions, the amount of leadership density was virtually identical across the two interactional rules. However, at about the halfway point, there was a clear differentiation between the density trajectories across the two rules. Specifically, in the model in which interactions were driven by contextualized identities, the positive slope of density accelerated. Descriptively, there was a greater increase in

new leadership connections in the model in which interactions were driven by contextualized identities in the second half of interactions.

Leadership centralization. In the first half of the team member interactions, leadership centralization was marginally lower for teams in the model in which interactions were driven by contextualized identities. Furthermore, in the first half of interactions, the slope was similar across both models. However, similar to leadership density, in the second half of interactions, there was a clear acceleration in the decrease of centralization, only for teams in the model in which interactions were driven by contextualized identities.

Leadership rating agreement. Teams in both models had a similar level of leadership rating agreement in the early interactions. However, teams in the model in which interactions were driven by contextualized identities had a much steeper increase in leadership rating agreement over time. Both types of teams decelerated in their increase in agreement over time, but teams in the model in which interactions were driven by contextualized identities ended with higher agreement.

Social Cognitive Perspective

OFAT sensitivity analysis for the role of self-schemas. To assess the role of leader and follower self-schemas, I first had to create a dataset that systematically varied across all possible values of the leader and follower self-schemas. The original dataset already included a set of leader and follower self-schema values that were based on past empirical data. I used the same values for this simulation. However, to assess the independent role of self-schemas on the study outcomes, I held the other individual elements (e.g., ILT) at the sample mean value. The final dataset used for the sensitivity analysis, therefore, had 500 teams. I proceeded to test the role of both leader and follower self-schemas on the three primary study outcomes. Agents again had a

total of 500 interactions. Therefore, the role of leader and follower self-schemas was assessed at three specific periods, early (at interaction 100), middle (at interaction 250), and late (at interaction 500). To understand the respective role of leader and follower self-schemas at the team-level, I chose to represent it as three variables: (1) Leader self-schema, (2) Follower self-schema, and (3) leader-follower self-schema difference (absolute difference). These variables were chosen as they represent three roles of self-schema, presented in the introduction of this paper, and covered in the broader literature (Epitropaki et al., 2017, Lord et al., 2016). Specifically, I theorized that self-schema should have a meaningful influence separately across, leader self-schema, follower self-schema, and the difference across the two perspectives. Because team compositional variables can be represented two primary ways—mean and variability (Bell, 2007)—the results are separated across two sets of graphs. The results for the mean of the self-schema variables are displayed in Figure 3 and the variability of these variables in Figure 4. I now describe the influence of each conceptualization of self-schema (leader, follower, and self-schema difference) across each of the three outcomes separately. I first report the results for the mean (i.e. mean leader self-schema, mean follower self-schema, mean self-schema difference), followed by variance (variance of leader self-schema, variance of follower self-schema, variance of self-schema difference).

Leadership density. As displayed in the top row of Figure 3, mean leader self-schema, follower self-schema, and self-schema difference did not have much of an influence on leadership density at any of the time points. The one unique example is at time 500, where teams with greater mean leader self-schema had greater leadership density.

As displayed in the top row of Figure 4, variability in leader self-schema, follower self-schema, and self-schema difference did not influence leadership density at any of the time points.

Leadership centralization. As displayed in the middle row of Figure 3, mean leader self-schema, mean follower self-schema, and mean self-schema difference did have some influence on leadership density across most of the time points. Mean leader self-schema had a consistent negative linear relationship with leadership centralization. Teams with higher mean leader self-schema had lower centralization than teams with lower mean leader self-schema. The relationship between mean follower self-schema and centralization was not consistent. At interaction 100, mean follower self-schema had no influence on centralization. However, after interactions 250 and 500, teams with higher mean follower self-schema had less centralization. Finally, the mean of self-schema differences did not have a consistent relationship with leadership centralization. However, there is some evidence that at time 100, teams with large differences had more centralization. In contrast, at later time points, teams with both low and high mean self-schema differences had higher centralization.

As displayed in the middle row of Figure 4, variability in leader self-schema, variability in follower self-schema, and variability in self-schema difference did appear to have a consistent influence on leadership centralization. Follower self-schema variability had a positive relationship with centralization over time, with the differences being the strongest at low and high values of follower self-schema variability. Teams with very low follower self-schema variability had low values of centralization, and teams with very high follower self-schema variability had high values of centralization. Leader self-schema variability had a consistent, positive relationship with centralization. Across all interactions, teams with more leader self-schema variability had greater centralization. Within-team self-schema difference variability had a clear influence on centralization, but only at interactions 100 and 250. Apart from very low variability, there was a descriptively strong negative relationship with centralization. Teams with

higher self-schema difference variability had lower centralization than teams with low self-schema difference.

Leadership rating agreement. As displayed in the bottom row of Figure 3, mean leader self-schema, mean follower self-schema, and mean self-schema difference did not consistently influence leadership rating agreement. However, there were two notable expectations. At interaction 100, teams with lower mean follower self-schema tended to have lower leadership rating agreement. Finally, at 500 interactions, there is a u-shaped relationship between mean self-schema difference and leadership rating agreement. Teams with low and high self-schema difference had higher leadership rating agreement compared to teams in the middle.

As displayed in the bottom row of Figure 4, variability in leader self-schema, and variability in follower self-schema had an influence on leadership rating agreement. Leader self-schema variability had a positive relationship across all time points, with teams higher in leader self-schema variability having higher leadership rating agreement. Follower self-schema variability had a similar relationship with leadership rating agreement. Within team variability in self-schema difference did not have a clear relationship with leadership rating agreement.

OFAT sensitivity analysis for SCP interactional rule. As discussed previously, the social cognitive perspective's central interactional rule is that individuals switch from using ILT to make leadership judgments, to an ILT that is weighted based on the other interactions that they observe. To assess the influence of this interactional rule, I created two datasets: one with the same parameters from the hypothesis testing (i.e., weighted ILT as the dominant rule; hypotheses 2A-2H), and a second that included the identical individual-level element value input parameters, but I changed the interactional rule so that it continued to use the ILT-other

characteristic matching from the early interactions. Consequently, any differences in outcomes could be isolated to the weighted ILT interactional rule.

To visualize the influence of the international rule on outcomes over time, I created a time-series graph using the same protocol as the previous perspective, amounting to 42 total periods. The results are displayed in Figure 5.

Leadership density. Teams in the model in which interactions were based on using weighted ILT quickly had a larger slope in leadership density compared to teams in the model based on normal ILT-characteristic comparison.

Leadership centralization. Teams in the model in which interactions were based on using weighted ILT had a lower centralization intercept. This represents the point at which teams had already had over 20 interactions. Although both models had a decrease in centralization over time, teams in the model in which interactions were based on using weighted ILT had a larger negative slope, representing larger decreases in centralization over time.

Leadership rating agreement. Teams in the model in which interactions were based on using weighted ILT also had a lower agreement in leadership ratings. Both models had a large increase in agreement over time. However, any difference in slopes across models appeared small.

RB Sensitivity Analyses Testing Elements of Each Perspective

To compare the relative influence of the core element in the social interactionist perspective (leadership structure schemas) to the core elements in the social cognitive perspective (leader and follower self-schemas), I first built two identical agent-based models. These base models had the same basic parameters from the ABMs used in the hypothesis testing (i.e. six agents, 500 interactions), and the element and interactional rule for the "base model"

listed in Table 3. Next, for the social interactionist ABM, I added leadership structure schemas, and for the social cognitive model, I added leader and follower self-schemas. For each model, I simulated 500 teams. I used the team-level data at the final time point for the analyses I discuss below.

Core elements of social interactionist perspective. To assess the influence of leadership structure schemas on the three primary outcomes in the study (i.e. density, centralization, and leadership rating agreement), I included the proportion of leadership structure schemas in separate linear regression models for the three outcomes. Results are shown in Table 7A. At the team-level, leadership structure schemas had a small effect on both leadership density (R^2 = .06), and leader rating agreement (R^2 = .06). Additionally, it had almost no influence on leadership centralization (R^2 = .00).

Core elements of social cognitive perspective. To assess the influence of leader and follower self-schemas on team outcomes, I performed three separate linear regression models, with leader and follower self-schema as predictors. Since these elements are represented at the team level, I chose two common team compositional representations (Bell, 2017) as predictors: mean and variance. Results are shown in Table 7B. To assess for the respective contribution of each predictor, I focus on the semi-partial correlation squared (sr^2). Across all outcomes, variance in leader and follower self -schema did not have an influence. Thus, I focus on interpreting the influence of average leader and follower self-schema. For leadership density, leader self-schema had a large influence (sr^2 = .43). Follower self-schema had a small influence (sr^2 = .09). For centralization, leader self-schema had a medium influence (sr^2 = .23), and follower self-schema had a small influence (sr^2 = .11). Finally, for leadership rating agreement both leader self-schema (sr^2 = .05) and follower self-schema (sr^2 = .09) had a small influence.

Result Summary

Table 8 summarizes the results from the hypothesis testing sections across the two theoretical perspectives. For each hypothesis, I present the results in terms of both statistical significance and effect size.

Discussion

The purpose of this research was to utilize agent-based modeling and simulation to investigate the two dominant process-oriented frameworks of leadership emergence. I now summarize the findings for hypothesis tests and sensitivity analyses, noting where results fit into existing leadership emergence theory. I then use these findings to develop a conceptual road map in which I describe three major themes that help integrate the two perspectives. In doing so, I aim to catalyze the development of an integrative, well-defined, and empirically guided theory of leadership emergence.

Findings for Hypothesis Testing

Social interactionist predictions. All seven predictions for this perspective were supported, providing initial evidence that my agent-based model is an accurate representation of the theoretical perspective. These results provided a necessary foundation for the next investigative step—interpreting how the core elements of this framework influence collective outcomes. All results are interpreted in reference to Table 8.

At the individual level, although there was support for both hypotheses concerning Leadership Structure Schemas (LSS; Hypotheses 1A and 1B), the effect sizes were small. Interestingly, the effect sizes were larger for the influence of LSS on follower role than leader role. This aligns with the early findings that LSS were significantly correlated with follower scores but not leader scores. This finding has some support from past theory from this perspective. A person's LSS is not theorized to influence the initial ILT-self characteristic comparison process that determines whether a person will claim leadership (DeRue, Ashford, & Cotton, 2009). Instead, LSS influence whether individuals perceive leadership as singular or plural (DeRue & Ashford, 2010). As represented in the ABM, this directly influenced granting

behavior (i.e., follower role), because individuals that first claim leadership will not grant leadership if they have a hierarchical LSS. This may have an influence on leadership *dyadically,* as a grant by one person reinforces another person's claim of leadership (DeRue & Ashford, 2010). However, as hypotheses 1A and 1B were focused at the individual level, these findings suggest that future work should investigate the influence of LSS at the dyadic level, in terms of leadership roles.

The results from Hypothesis 1C supported the theorized claim that having more individuals with shared LSS on the team increases the amount of followership on the team, resulting in more shared forms of leadership (DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009). Overall, the results for the LSS hypotheses had small effect sizes, suggesting that another element is more influential on team outcomes. The results for hypothesis 1D supported this supposition, as the association between ILT-self comparisons and shared leadership had a large effect size. This finding is noteworthy because works within this perspective (e.g., DeRue et al., 2015; DeRue & Ashford, 2010; Marchiondo et al., 2015), focus primarily on what drives the dyadic processes of leadership emergence, not this individual-level comparison process. Thus, future work should further incorporate the role of ILT-self comparisons in leadership emergence.

Results for Hypothesis 1E indicated that more shared leadership occurred on teams with smaller within-dyad comparisons. As the effect size for this finding was substantial, this suggests that ILT were influential on the process of leadership emergence at the individual level as well as the dyadic level, providing initial empirical support for the importance of ILT in the leadership emergence process under this perspective.

Finally, results for Hypotheses 1F and 1G indicated that individuals developed stable, contextualized leader and follower identities over time. I noted descriptively that both leader and follower identity means were high, whereas the standard deviation was lower than leader identity. Taken together, it appears that most individuals tended to develop follower identities over time, but there was more variability across leader identity. This finding may reflect that, in my model, individuals evaluated others' attempts to enact a leader role, but not a follower role (i.e., expectations for followers; IFTs).

Social cognitive predictions. As six of the eight predictions for the social cognitive perspective were supported, the results provided initial support that my agent-based model was an accurate representation of this perspective. These results provided a necessary foundation for interpreting how the core elements of this perspective influence collective outcomes. All results are interpreted in reference to Table 8.

Although there was support that leader and follower self-schemas influence leadership outcomes at the individual level (Hypothesis 2A), these effects were small to medium. The concept of self-schema has existed for decades (Markus, 1977), but the idea that individuals will use relative comparisons between leader and follower self-schemas is recent (Epitropaki et al., 2017). As such, these findings provided initial support that these comparisons would have an influence on the enactment of leadership (e.g., Lord, et al., 2016). The results of Hypothesis 2B suggest that, at the team level, leader self-schemas are more influential than follower self-schemas for team outcomes; a conclusion further tested with sensitivity analysis.

Results for Hypothesis 2C showed that between-dyad differences in ILT-other comparisons were associated with less shared leadership. I argue that this makes a meaningful contribution to the literature, as most work has focused on within-dyad congruence (Epitropaki,

et al., 2013). Additionally, as my ABM was focused on within-dyad interactions, between-dyad interactions were not explicitly modeled. This result addresses the call for additional research examining the role of ILT beyond the dyadic level (Epitropaki, et al., 2013), and suggests that ILT might be influential for team processes to a similar extent as dyadic processes.

Hypotheses 2D and 2E from this perspective addressed the rate at which teams emerged over time. These hypotheses were the only two that were not supported. Literature on emergence points to a substantive reason for these non-significant results. Complexity theory would suggest that emergence is more difficult to measure than a unitary construct such as shared leadership (Dinh et al., 2014; Uhl-Bien, Marion, & McKelvey, 2007). Despite the growing literature on measuring collective forms of leadership (Zhu, Liao, Yam, Johnson, 2018), scholars are still unclear on best practices to measure emergence (Kozlowski, 2015). This ongoing challenge in measuring emergence may provide insight for the lack of support for Hypotheses 2D and 2E.

Support for Hypotheses 2F and 2G illustrated increasing stability in leader and follower identities over time, with medium-large effect sizes. As indicated in the descriptive statistics for this perspective, the leader and follower identities at the final time point were large and not variable. These results may be a function of the role of self-schemas, as in my prior work (Acton & Foti, 2019), individuals tended to be schematic on both leadership and followership. These data represented the starting parameters of the current agent-based model and may reflect the importance of starting parameters in ABM (Grimm et al., 2010).

The finding that leadership rank became more stable over time (Hypothesis 2H), generates two conclusions. First, the results should be viewed as compelling evidence for the importance of the ILT weighting process (Acton et al., 2019). If all individuals shift their initial ILT to one that aligns with the team, each person's ILT should become more similar to one

another's over time. As ILT inform leadership perceptions, these perceptions should also become more consistent over time. Second, the correlations of leadership rankings became descriptively smaller over time, suggesting larger changes between time points early on. This result fits with complexity theory that emergence is a non-linear process, with the initial period being critical to system changes (Guastello, 2007; Plowman et al., 2007).

Findings for Sensitivity Analyses

I now summarize the results of each type of sensitivity analysis (OFAT and RB) separately. For each type, I first discuss the results for the social interactionist perspective, followed by the social cognitive perspective.

OFAT sensitivity analysis for the social interactionist perspective. Leadership structure schemas (LSS) had a consistent influence across leadership outcomes (Figure 1). Consistent the social interactionist perspective, teams with a greater proportion of people with shared LSS had more shared leadership (DeRue & Ashford, 2010). However, past theory is not clear *when* LSS should influence the leadership process. As the graphs for the OFAT sensitivity analysis indicated, LSS had a descriptively greater influence over time. This result aligns with complexity theory, which suggests that individual elements increase in influence over time because of the self-reinforcing nature of early interactions (Plowman et al., 2007; Schneider & Somers, 2009).

From comparing the average trajectories of leadership outcomes over time (Figure 2), the results illustrated interesting findings that both align with past theory and generate new ideas. Aside from a few exceptions (e.g., DeRue et al, 2015), empirical work has found that leadership distributions become more shared and less centralized over time (Berdahl & Anderson, 2005; Drescher, Korsgaard, Welpe, Picot, & Wigand, 2014; Small & Rentsch, 2011). The results from

the ILT comparison model produced this expected pattern. This is noteworthy because contextualized identities were not included in this model. These results suggest that team members will identify which individuals have characteristics that best fit the leadership expectations of others (i.e., ILT; Shondrick et al., 2010). Therefore, a leadership structure emerged to some degree, even without the inclusion of contextualized leader and follower identities in the model.

When interactions were driven by contextualized identities, the slopes of outcomes kept the same overall patterns as the previous model but increased in their rate of change. This result supports the idea that contextualized identities influence the process of leadership emergence beyond ILT-other comparisons, as reflected by steeper slopes in leadership agreement over time (Kwok, Hanig, Brown, & Shen, 2018). As the slopes between models (Figure 1) became more different over time, these results align with prior literature which suggests that the contextualized identities become critical to leadership *over time* (Emery et al., 2011). Finally, it is important to note that when interactions were driven by ILT only (i.e., identities not included), outcomes tended to reach a point of stability. Taken together, these results provided support for the concept of identity as a driver of interactions, as identity represents what dynamical systems approaches would label an attractor state (Gorman, Amazeen, & Cooke, 2010). Within a dynamic system, attractor states represent points that individuals consistently shift to (Vallacher Coleman, Nowak, Bui-Wrzosinska, 2011). Applied to the current work, identities represent an attractor state that becomes stronger over time. As identities become stable, individuals perform consistent claiming and granting patterns.

OFAT sensitivity analysis for the social cognitive perspective. Leader and follower self-schemas did not have a consistent pattern of associations with leadership outcomes (Figures

3 and 4). For each outcome, there were minimal associations that were consistent with prior literature. Regarding leadership density, only average leader self-schema was influential. This result aligns with past theory, which suggests that leader self-schemas are critical in the establishment of new leadership connections (Murphy, Reichard, & Johnson, 2008). For leadership centralization, leader self-schema again had the most consistent influence, with lower mean and higher variability in leader self-schema associated with greater leadership centralization. This supports expectations, as teams with less people associating themselves with leadership, and more variability across people in these associations should amount to a more centralized leadership structure (Mehra, Smith, Dixon, & Robertson, 2006). Follower self-schema variability also had a positive association with leadership centralization. This provided support to theory that suggests that a team with many individuals being willing to lead, but not follow, will result in a more centralized form of leadership (DeRue, 2011). For leadership rating agreement, the major conclusions were similar to the findings for centralization, in that both leader and follower self-schema *variability* had a consistent positive association with leadership rating agreement. This supported the earlier finding that rating agreement was most influenced by how much *difference* there was across people, a point I address in a later section.

From comparing the average trajectories of leadership outcomes over time, the results were mostly consistent with expectations from the social cognitive perspective. Overall, both models in this perspective (i.e., ILT comparison, weighted ILT), produced expected trajectories, with leadership becoming more shared and less centralized over time (e.g., Berdahl & Anderson). For leadership density, there was a larger slope for teams whose interactions were driven by a weighted ILT, aligning with theory. As individuals transition to using an ILT that is weighted by what they observe, this weighted ILT becomes closer to an average of the ILT of all

individuals on the team. If individuals have a somewhat normal distribution of leadership characteristics (Epitropaki & Martin, 2005), this average ILT should closely align with the observed leadership characteristics of *more* individuals (i.e., greater congruence). As ILT congruence drives leadership perceptions (Engle & Lord, 1997), the inclusion of an ILT weighting process should have resulted in the observed large increase in leadership connections.

Notably, leadership rating agreement was not influenced by the weighted ILT rule in the expected fashion. Although agreement increased over time, which was expected, the intercept of the observed trajectory was lower than the trajectory from the normal ILT comparison model. This result may have been influenced by the transition to a weighted ILT (at stage two of the simulation), resulting in discontinuity from previous interactions, which led to a decrease in agreement. However, theory would suggest that a weighted ILT would be a catalyst to emergence, similar to the role of identity in the previous perspective (Acton et al., 2019). This did not occur, as the slope was descriptively similar for the weighted ILT model compared to the normal ILT model.

RB sensitivity analysis for both perspectives. The OFAT sensitivity analysis held the other individual elements constant when assessing the role of LSS, for which there was a clear and consistent relationship with leadership outcomes. The RB analysis presented a different result when accounting for other factors, as the amount of variance accounted for by LSS was small. When paired with the results for hypotheses 1A-1E, these findings illustrate that ILT and leadership characteristics have a greater influence on leadership outcomes than LSS. These results may be a function of how LSS were represented in the simulations, an important point I return to in a later section.

The results of the OFAT sensitivity analyses illustrated that leader and follower self-schemas influenced outcomes, though the level of influence was not clear. The results from the RB sensitivity analysis presented a different conclusion, with leader self-schema accounting for large variance in outcomes. These findings align with the results from Hypotheses 2A and 2B, which illustrated that leader self-schema was an important component within the social cognitive model. Additionally, these findings aligned with the results from Hypotheses 2B in that follower self-schema did not have a large influence on leadership outcomes. Overall, leader self-schema appeared to have a greater influence than LSS. I further discuss the implication of these findings in a later section.

Integration of Findings

Given the numerous findings from this work, it is necessary to organize and integrate results to advance the study of leadership emergence. As such, I structure the rest of my discussion around three central themes: (1) the current representation of leadership emergence, (2) the integration of individual-level elements, and (3) the integration of interactional rules. I finish by discussing strengths, limitations, and future directions.

Current representation of leadership emergence. From hypothesis testing, the most notable findings were the results of the two hypotheses (hypothesis 2D and 2E) related to emergence over time. Both predictions were not supported. These unexpected results yield an important concern in the study of leadership emergence, which is whether the literature's current measurement and conceptualization of leadership emergence is accurate. I discuss these points in further detail below.

Measurement of leadership emergence. In the current work, I used a formula that was based on an intraclass correlation (ICC 1), which is a common metric used to capture emergence

within the teams literature (Bliese, 2000; Kozlowski, 2015). This metric captures the amount of variance that is accounted for by a specific source (e.g., team membership; Bliese, et al., 2018), which I used to represent agreement in leadership ratings. The greater the ICC value, the more agreement towards individuals in leadership ratings.

ICCs are effective for capturing emergence, as this metric accounts for variability both within and *across* units (i.e., people; Bliese & Hanges, 2004). However, recent work by Lang and colleagues (Lang & Bliese, 2019; Lang, Bliese, & Runge, 2019) has elucidated limitations in using ICCs to capture emergence. Among these limitations, a critical issue is that ICC values can increase for two reasons: an increase in variability between units, or a decrease in variability within a unit (Lang & Bliese, 2019). Interpreted in the context of the current study, the increase in ICCs for leadership rating agreement may not necessarily indicate consensus in these ratings (i.e., emergence). Instead, these values could indicate more variability across people in leadership ratings.

In their work, Lang and colleagues (Lang & Bliese, 2019; Lang et al., 2019) introduced a multilevel modeling procedure that the authors argue can better capture emergence over time than ICCs. Lang and colleagues introduced a three-level, mixed-effects model with a time-person-team nested format. Using this model, researchers can test whether variance in ratings within a team is significantly decreasing over time (Lang et al., 2019), which would indicate emergence.

Finally, Lang and colleagues (Lang et al., 2019) discussed how predictors can be included in this three-level model. I argue that this novel methodology will allow scholars in this area to test research questions that have not yet been possible to investigate under current methods. Specifically, by adopting a similar three-level model for leadership emergence, future

work can assess whether individual elements (e.g., ILT) predict the extent to which leadership emerges in teams. In the current literature, most works study the form of leadership (i.e., shared leadership) and not the level of consensus (Acton et al., 2019). As such, there is a large body of research about the influence of individual elements on collective leadership (Wang, Waldman, & Zhang, 2014), but research on the role of these elements in the emergence process is scarce. As such, capturing emergence using Lang and colleagues' methodology has the potential to advance the study of shared leadership.

Conceptualization of leadership emergence. In addition to raising measurement concerns, the lack of support for hypotheses 2D and 2E raise questions about the association between the leadership structure (e.g., shared leadership) and the emergence of shared leadership perceptions. The growing literature on shared leadership often assumes that leadership has emerged within the team (Nicolaides, Laport, Chen, Weis, & Zaccaro, 2014). If leadership is shared, it is viewed as a specific form or pattern of leadership in which individuals freely share leader and follower roles (DeRue, 2011). In hypotheses 2D and 2E, I predicted that more shared expectations would result in emergence happening more quickly. These predictions were not supported.

Although the lack of support is seemingly inconsistent with theory in leadership, it aligns with theory on emergence (e.g., Anderson, 1999; Byrne, 2005). In their book on the philosophy of emergence, Bedau and Humphreys (2008) define an emergent system as having features that are unique from its parts. More updated literature describes emergence as evident only if the macro-level unit (i.e., team) has a clear structure (Luria, 2019). A fully shared form of leadership may not fit this requirement of emergence. In the current study, some teams developed fully shared forms of leadership, represented by individuals who performed both leader and follower

roles every time they were in an interaction. Following the literature on the philosophy of emergence (Gillett, 2016), it seems unlikely that leadership emerged in these teams because the structure of leader and follower roles was not clear. Specifically, everyone enacted leader and follower roles. In the current work, leadership did not appear to emerge in teams with fully shared forms of leadership, which I posit may be due to the lack of structure in leader and follower roles.

Based on the above findings, I argue for the reconceptualization of emergence that treats it as an event-level phenomenon. Specifically, the results of this work align with the conceptualization of leadership emergence as psychological entropy (Acton et al., 2019). Originally introduced by Hirsh and colleagues (Hirsch, Mar, & Peterson, 2012), psychological entropy adapted the concept of entropy—the level of uncertainty within a system—to an individual's cognitive system. Entropy is the number of possible microstates that a system can maintain. As such, maximum entropy is a system with maximum uncertainty (Shannon, 1948). Psychological entropy is discussed in terms of decision-making contexts (Hirsh et al., 2012). Hirsh and colleagues give the example of a person getting a flat tire. A person with a flat tire has multiple options for a potential problem-solving action. Based on past experiences, if one action was the clear best option, this would represent minimal entropy, and a decision would be quickly made.

Psychological entropy has important implications for studying an emergent system, as emergence requires some level of entropy. Thus, a system with no activation (i.e., restful state) does not represent emergence (Bedau & Humphreys, 2008). In the context of leadership, a team in which no individuals were performing a leader role (DeRue, 2011) would represent a system with no activation. However, for a collective structure to emerge, a system shifts from maximum

to minimal entropy (Hirsh et al., 2012). If the system has maximum entropy, then the system will be unable to take a required action. At the individual level, this is the case where "one has absolutely no idea what is happening or what one should do" (Hirsh et al., 2012, p. 312).

Translating the concept of psychological entropy to leadership emergence, each decision option in the system can be represented by each person as a potential leader on the team (Acton et al., 2019). At each point of team interaction, every person can be represented in terms of his or her probability of enacting leadership. See Figure 6 for a visual representation of a team with low entropy at one interaction point. In Figure 7, I also represent how entropy in team leadership is represented across multiple interactions. This visualization helps provide an explanation for how a fully shared form of leadership may not represent an emergent system. As presented in Figure 7, as teams interact over time, two different types of shared leadership can occur, one in which leadership has emerged, and one in which it has not. In Figure 7, the first picture (at the top) represents a team in which each person (represented by x) has an equally high probability of enacting leadership at each time point. Aggregated across time, this would indicate a shared form of leadership, as all individuals are participating in the leadership process. However, this pattern of leadership *would not* indicate an emergent structure, as there is maximal entropy and thus uncertainty about who will perform the next leadership act. Also in Figure 7, the second picture (at the bottom) represents a team where only one person (represented by x) has a high probability of enacting leadership at each time point. If this consistent pattern of leadership continues over time, all individuals are actively participating in the leadership process. As such, this would again indicate a shared form of leadership. This pattern of leadership *would* indicate an emergent structure, as there is minimal entropy and thus certainty about who will perform the next leadership act.

Finally, it is important to note that these ideas are not completely new. Notably, Contractor and colleagues (2012) introduced a similar event-based conceptualization of collective leadership, which focuses on how multiple individuals transition between leadership roles over time. I argue that my conceptualization builds from this past work by discussing the mechanism by which these transitions occur—through the reduction of cognitive uncertainty about the next leadership act (Hirsch et al., 2012). Furthermore, this updated conceptualization was generated from the lack of support for hypotheses 2D and 2E. It should be noted that this conceptualization cannot be represented using the agent-based models I designed for this work. I address this in the limitations section.

Integration of individual-level elements of leadership emergence. One of the primary goals of this work was to test the utility of each individual-level element in the leadership emergence process with a focus on the unique elements across the social interactionist and social cognitive perspectives. Results generate two important conclusions that can assist in the integration of leadership elements into a comprehensive theory.

First, the models from each perspective demonstrated largely similar results for leadership outcomes. However, the results from the previous analyses illustrate that the individual elements that were most influential for leadership outcomes were different for each perspective. For the social interactionist perspective, ILT-self comparisons had a large influence on leadership outcomes (hypotheses 1D and 1E). Further results indicate that LSS had a small influence on leadership outcomes. For the social cognitive perspective, leader self-schemas had a large influence on leadership outcomes. Taken together, though results from each perspective yield overall similar findings, different individual-level variables were responsible for these outcomes. These opposing explanations present a direction for future research that is necessary

for the development of an integrative theory. Relatedly, Vancouver and Weindhardt (2012) introduced a process for comparing two frameworks. Stage one involves using modeling to identify the unique elements of each framework. Results from the current work indicate that for the social interactionist perspective, ILT-self comparisons uniquely explain leadership outcomes, whereas for the social cognitive perspective, this unique explanatory variable is leader self-schemas. Stage two involves identifying a scenario in which each model makes a different prediction and testing each prediction using empirical data. Applied to this work, the two unique elements for each perspective present a scenario that would yield opposing predictions. In the social interactionist model, ILT had a large influence on the enactment of a leadership role. Opposingly, for the social cognitive model, ILT did not have a meaningful influence on leader roles, as evidenced by the nonsignificant correlation between ILT and leadership scores. Future work can test these competing predictions by collecting data using real-life teams.

Second, an important conclusion from the current results was the lack of influence that LSS had on the study outcomes. Specifically, the sensitivity analysis indicated that LSS account for a small amount of variance in leadership outcomes. These results have essential implications for theory development on leadership emergence. In developing an integrative theory, the conceptualization of LSS needs to be revisited to ensure accurate portrayal in a model of leadership emergence. The model in the current work represented LSS based on the original discussion in DeRue and Ashford (2010). In this description, people who first claim leadership will be unlikely to grant leadership to others if they have a hierarchical LSS. However, the current work does not represent other possibilities, including a person who grants leadership and is then unwilling to claim leadership because she has a hierarchical LSS (DeRue & Ashford, 2010). As a result, future work needs to reassess whether different conceptualizations of LSS

increase its influence on the claiming and granting process. This idea also requires greater specificity in theory regarding how LSS consistently influences the process of leadership emergence.

Integration of interactional rules of leadership emergence. The results of the sensitivity analyses provide multiple opportunities for integration across the unique interactional rules for both perspectives. For most outcomes, the interactional rules for each perspective produced expected results. However, for the social cognitive perspective, using a model in which agents base their grants on a weighted ILT did not produce expected trajectories for leadership rating agreement. This provided evidence that this rule may not be sufficient for representing emergence over time. Future work can further test this by applying the approach presented by Vancouver and Weindhardt (2012) to studying the social cognitive perspective's interactional rule (i.e., weighted ILT) in relation to the social interactionist perspective's interactional rule (i.e., contextualized identities). As the results for the social cognitive framework illustrated, through the ILT weighting process, team members are expected to adjust their ILT to become more similar to each other over time. This idea could be tested by studying teams that have worked together and have an emergent leadership structure. Based on the ILT weighting process, the social cognitive framework would predict that, for these teams, a person whose characteristics align closest with the *average* ILT of the group would be most likely to be perceived as a leader. The social interactionist perspective would not predict this, as leadership perceptions become based on a contextualized follower identity (DeRue & Ashford, 2010). Consequently, if future work tests the above prediction, results would either support one of the two interactional rules as the more accurate representation of the leadership emergence process.

Although the above idea for a study represents a "strong inference" approach (Platt, 1964), Vancouver and Weinhardt (2012) also described scenarios in which opposing models may address "different issues" that they apply in unique contexts. Rather than eliminating one model in preference for another, this scenario allows for integration. According to work on social identity theory (van Knippenberg, 2011), group members vary in the extent to which they identify with the group. The stronger their identification, "the greater the importance of group prototypes" for leadership perceptions (van Knippenberg, 2011, p. 1080). Under this view, the interactional rules from both the social interactionist and the social cognitive perspective can co-exist. In teams where members do not strongly identify with the group, I argue that members will base their leadership judgments on their contextualized follower identity using the social interactionist rule. In teams where members strongly identify with the group, I argue that these members will base their leadership judgments on a weighted ILT using the social cognitive rule.

Strengths, Limitations, & Future Directions

In my comprehensive effort to formally model and test two process-oriented perspectives of leadership emergence, I believe there are multiple strengths to this work. First, this work directly answers recent calls to investigate the role of leadership schemas (e.g., ILT) in dyadic processes of leadership (Lord, Foti, Epitropaki, & Keller Hansborough, 2020). Second, in utilizing agent-based modeling, this work addresses the call to utilize new methodologies for studying the dynamic processes of leadership (Castillo & Trinh, 2018). Finally, many prominent leadership scholars have argued that there are too many theories seeking to explain the same leadership phenomena (Antonakis, 2017; House & Shamir, 1993; Lord, 2017). Meuser and colleagues (2016) argue that leadership emergence research in particular requires substantial efforts for integration across theories. I argue that the current work addresses these calls for

integration in two ways. First, I translated two dominant perspectives into formal models that can be compared to each other, and second, in summarizing the results, I presented multiple research directions that can lay the foundation for integrating these perspectives into a combined formal theory of leadership emergence.

Although comprehensive in nature, this work contains multiple limitations, many of which offer an opportunity for future research. Most narrative theories are either too abstract to be adapted into a formal model, or they are too inconsistent across different works (Macal & North, 2009). As a result, the modeler must make difficult choices in building their model, which may result in it not aligning with theory (Terano, 2008). Second, even when there is information available, the modeler must prioritize model simplicity because model complexity results in difficulty drawing meaningful conclusions (Smith & Conrey, 2007). The process of building an agent-based model thus becomes a balance between incorporating all critical elements and rules, and keeping the model simple (Alexrod, 1997; Terano, 2008). By aiming for model simplicity, this work may have been limited by oversimplification.

The influence of an external environmental was likely the most impactful parameter absent from the model. Although top-down influence was modeled indirectly through the social context of other team members, the simulation did not include a task. Teams operate within the context of a task that provides goals; these goals then impact interactions (Grand et al., 2016). Incorporating a task environment has direct implications for the event-level conceptualization of leadership emergence that I introduced. For Figure 7, each box could represent what Hirsch and colleagues (2012) call minor goals. These minor goals would then be determined by a major goal (Hirsch et al., 2012), representing the team's overall objective during the task. These ideas can be represented by an agent-based model, with teams completing a series of minor goals over the

entire simulation. Hirsch and colleagues (2012) argue that failure to address a specific minor goal can cause an increase in entropy, resulting in greater uncertainty in later goals. Adapted to leadership, this would represent a team with a stable leadership structure that begins failing to effectively complete goals, resulting in increased entropy. As emergence is represented by decreases in entropy (Borge-Holthoefer et al., 2016), this team would address goal failure by adopting a new leadership structure.

The current work excluded many other theoretical constructs discussed across each perspective. This work did not include implicit follower theories, or the expectations that others have for followers (Sy, 2010). I also focused on prototypical implicit leadership theories and did not include the other forms of ILT discussed in the literature (Epitropaki et al., 2013). Finally, there was no formal ranking included in any of the models (i.e., organizational hierarchy). I hope that future research can build from this initial work by including these other model elements.

Finally, this work focused on two dominant theoretical perspectives, but neglected social identity perspective, a major area in the study of leadership and teams (e.g, Hogg & van Knippenberg, 2003). I chose not to incorporate this perspective into this work as research applying social identity to leadership does not model group interaction, but rather the cognitive processes by which group membership influences leadership perception. The core assumptions (e.g., dyadic interaction) I used to design the agent-based models in this work would thus not be an accurate representation of this perspective. Nevertheless, future work should incorporate how specific ideas from social identity theory might inform an integrative theory of leadership emergence.

Conclusion

In the current work, I attempted to utilize agent-based modeling and simulation to test and integrate two process-oriented frameworks of leadership emergence. In doing so, the results present multiple themes about the current strengths, challenges, and opportunities regarding current conceptualizations of leadership emergence. I hope that these themes offer a road map that can lead to a great advancement in the study of leadership emergence through the refinement of these ideas into a single, integrative theory.

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Appendix A
Outline of ODD Protocol (Adapted from Railsback & Grimm, 2019)

Concept	Description
Purpose	Provide a summary of the overall objective(s) for which the agent-based model was developed.
Entities, state variables, and time scales	Define stable elements, state variables that form through interaction, and outline the time scale that each iteration represents (e.g., weeks).
Process overview and scheduling	Define what happens within the simulation, and at which time step each event happens.
Design concepts	Describe important characteristics of the model design, including: - *Emergence:* What entities are created through emergence or non-linear generation. - *Stochasticity:* What aspects of the model created randomness, in that if multiple iterations of the same model are run (i.e., starting parameters), the outcome changes. - *Sensing/Learning:* Do agents learn from one another? If so, describe how this process occurs. - *Interaction:* How do the agents interact, including what level of interaction (e.g., dyadic) occurs.
Initialization	Define the starting parameters of the model and how they were generated

Appendix B
Items from Leader and Follower Self-Schema Scale

Item	Leader Self-Schema Items
1	I am able to recognize when a group requires my leadership.
2	I am able to remember times in which I performed leadership behavior.
3	I am prepared to exercise my leadership ability when needed.
4	I tend to notice when other people are looking to me for leadership.
5	I am able to remember how well I performed as a leader in past groups.
6	It is easy for me to gather the information necessary to perform as a leader.
7	I recognize when information is relevant to my ability to lead others.
8	I am able to remember times when others treated me as a leader.
9	I can make judgments or decisions about my leadership with relative ease.
10	I anticipate when my leadership is required in a group.
11	I am able to remember skills that help me be a leader.
12	I can quickly figure out what I need to do as a leader.

Item	Follower Self-Schema Items
1	I am able to recognize when my group needs me to follow others.
2	I am able to remember times in which I performed follower behavior.
3	I am prepared to exercise my ability as a follower when needed.
4	I tend to notice when other people are looking to me to follow them.
5	I am able to remember how well I performed as a follower in past groups.
6	It is easy for me to gather the information necessary to perform as a follower.
7	I recognize when information is relevant to my ability to follow others.
8	I am able to remember times in which others treated me as a follower.
9	It is easy for me to make judgments or decisions related to my role as a follower.
10	I anticipate when the group requires me to follow others.
11	I am able to remember skills that help me be a follower.
12	I can quickly figure out what I need to do as a follower.

Appendix C
Primary R Packages Used for Analyses

Package	Uses	Citation
"apaTables"	To produce many of the tables for the results section	Stanley (2018)
"data.table"	To combine all separate teams data into one large file used for data analysis	Dowle and Srinivasan (2019)
"dplyr"	To convert full data to form necessary for different levels of analysis	Wickham, François, Henry, and Müller (2020)
"effectsize"	To produce and help interpretation for effect sizes in linear models	Makowski, Ben-Shachar & Lüdecke (2019)
"ggplot2"	To produce all figures in this work	Wickham (2016)
"lm.beta"	To calculate standardized beta weights for linear models	Behrent (2014)
"MASS"	To simulate sample variables based on previous literature	Venables and Ripley (2002)
"nlme"	To analyze mixed-effects models including the growth models assessed in the current study	Pinheiro, Bates, DebRoy, Sarkar, R Core Team (2020)
"performance"	To calculate variance accounted for in mixed methods framework	Lüdecke, Makowski,Waggoner Patil (2020)

Table 1a

Agent Variables for the Social Interactionist ABM

Variable	Description	Level	Type
C_i	Individual Self-Attributes of Agent *i*	Individual	Entity
ILT_i	Implicit Leadership Theory of Agent *i*	Individual	Entity
LSS_i	Leadership Structure Schema of Agent *i*	Individual	Entity
LI_i	Leader Identity of Agent *i*	Individual	State
FI_i	Follower Identity of Agent *i*	Individual	State
LP_{ij}	Leadership Perception of Agent *i* Towards Agent *j*	Dyadic	State

Table 1b

Stepwise Interactional Rules for Social Interactionist ABM

Stage 1: Initial Interaction Based on Leadership Schemas	
Step	Description
1	Interaction clock is set to 0; each agent is assigned all entity variables.
2	Two agents (*i* and *j)* are randomly selected for dyadic interaction.
3	Each agent compares its ILT (ILTi) to Individual Attributes (Ci). The closer that ILT_i is to C_i, the more likely the agent claims leadership within that interaction.
4	Agent *j* compares agent i's Individual Attributes (Ci) to their ILT. The more similar it is to their ILT, the more likely they proceed forward in the evaluation process (step 5). Alternatively, they do not grant leadership.
5	If agent *j* has a shared leadership structure schema, they then grant leadership to the other person. If they have a hierarchical leadership structure schema, and they claimed leadership themselves already, they do not grant agent *i's* leadership claim (or if they have not claimed, they do grant).
6	Steps 4-5 repeat for agent *i* towards agent *j*.
7	Agent *i and Agent j* each change their leader identity score (LIi) from the previous iteration. They add 1 if they claimed and were granted leadership, subtract 1 if they did not claim and were not granted leadership. Any other result does not change the agent's LIi.
8	Agent *i and Agent j* each change their follower identity score (FIi) from the previous iteration. They add 1 if the dyadic partner claimed and they granted leadership, subtract 1 if the dyadic partner did not claim and they did not grant leadership. Any other result does not change the agent's FI.
9	Agent *i and Agent j* each change their LP score for each other from the previous iteration. If they granted leadership, they add .5 to their LP score for the other agent. If the other agent claimed leadership, they would add .5. If neither happens, the agent's LP score does not change towards that agent.
10	Each agent repeats Steps 2- 9 until they have had ten dyadic interactions *that they are involved in*. Once all agents have had ten interactions, the contextualized L-F identities become solidified and are now used as their criteria for claiming/granting leadership. The simulation proceeds to the next section.
Stage 2: Contextualized leader-follower identities now formed (After all agents have participated in ten interactions)	
Step	Description
1	Two agents (*i* and *j)* are randomly selected for dyadic interaction.
2	Each agent uses their contextualized leader identity to determine the probability that they will claim leadership; they then decide to claim or not claim leadership. The higher the identity, the more likely they claim.
3	Each agent uses their contextualized follower identity to determine the probability that they will grant leadership. They then decide to grant leadership based on this probability. The higher the identity, the more likely they grant.
4	Agent *i and Agent j* each change their leader identity score (LI) from the previous iteration. They add 1 if they the dyadic partner claimed and they granted leadership, subtract 1 if the dyadic partner did not claim and they did not grant leadership. Any other result does not change the agent's LIi.
5	Agent *i and Agent j* each change their follower identity score (FIi) from the previous iteration. They add 1 if the dyadic partner claimed and they granted leadership, subtract 1 if the dyadic partner did not claim and they did not grant leadership. Any other result does not change the agent's FI.
6	Agent *i and Agent j* each change their LP score for each other from the previous iteration. If they granted leadership, they add .5 to their LP score of the other agent. If the other agent claimed leadership, they would add .5. If neither happens, the agent's LP score does not change towards that agent.

Table 1c

Primary Simplifying Assumptions for Social Interactionist ABM

Assumption Type	**Simplifying Assumption**	**Conceptual Support**	**Citation(s)**
General	Dyadic interactions represent the core of leadership emergence	Double interacts are the core unit of interactions across multiple works	DeRue & Ashford, 2010; DeRue, 2011
General	Individuals first determine self-decisions (i.e. should I claim) before evaluating others	Original works discuss self-decisions as foundational to the leadership process	Acton et al., 2019; DeRue, Ashford, & Cotton, 2009
Unique to Perspective	Leader identity starts somewhere close to equal likelihood of claiming leadership, adjusted by how close the ILT-self characteristics comparison is	Individuals discussed as having past experiences as a leader and so this should affect their tendency to enact leadership	DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009
Unique to Perspective	Follower identity starts at the point where a person is equally likely to grant leadership and is socially constructed over time	Focus at the follower level, prior to identity being developed, is on leadership structure schemas as well as ILT, not a follower self-schema	DeRue & Ashford, 2010; Marchiondo, Myers, & Kopelman, 2015
Unique to Perspective	Those with a hierarchical LSS do not allow two people to serve as a leader within an interaction	Original examples used to represent LSS, describe it as clear standard for dyadic interactions early on	DeRue & Ashford, 2010
Unique to Perspective	Individuals strengthen their leader/follower identity when a claim is reciprocated with a grant	The development of a contextualized identity is a truly dyadic process in that it requires socially reinforced claims	DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009
Unique to Perspective	Individuals weaken their leader/follower identity when their non-claim/grant is reciprocated with a non-grant/claim	The opposite of the identity formation process is equally dyadic, in that a series of non-claims and grants results in a decline in identity	DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009
Unique to Perspective	Individuals leadership perception of others is increased both from when the grant leadership to others, as well as when the other person claims. However, if both occur then this will have most impact on leadership perception	Past cases are presented where individuals claiming leadership repeatedly can develop leadership roles independent of initial reinforcement of claims	DeRue & Ashford, 2010; DeRue, Ashford, & Cotton, 2009

Table 1d

Core Model Initializing Parameters for Social Interactionist ABM

Parameter	**Description**	**Parameter Level**	**Starting Value(s)**
ILTi	Implicit Leadership Theory	Agent	Range = 42 – 90
Ci	Prototypical Leadership Characteristics	Agent	Range = 10 – 90
LSSi	Leadership Structure Schema	Agent	0 (hierarchical) or 1 (shared)
Interaction Cutoff	How many interactions before rules change to Stage two	Environment	10
Leader Identity	Contextualized Leader Identity	Agent	(random 60 -80) – abs(ILT – Ci difference)
Follower Identity	Contextualized Follower Identity	Agent	50

Table 1e

Formal Predictions Tested in Social Interactionist ABM

Hypothesis #	Hypothesis
1a	*If an individual has a Hierarchical LSS, then that person will be perceived more as a leader.*
1b	*If an individual has a Shared LSS, then that person will perform more of a follower role.*
1c	*If teams have a greater proportion of individuals with shared leadership structure schemas, then the team will have a more shared leadership structure.*
1d	*If teams have smaller average differences in individual-level, ILT-to-self comparisons, they will have a more shared leadership structure.*
1e	*If teams have smaller differences in ILT-other comparisons within dyads, then they will have a more shared leadership structure.*
1f	*Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.*
1g	*Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.*

Table 2a

Agent Variables for the Social Cognitive ABM

Variable	Description	Level	Type
C_i	Individual Self-Attributes of Agent *i*	Individual	Entity
ILT_i	Implicit Leadership Theory of Agent *i*	Individual	Entity
LSS_i	Leadership Self Schema of Agent *i*	Individual	Entity
FSS_i	Follower Self Schema of Agent *i*	Individual	Entity
LI_i	Leader Identity of Agent *i*	Individual	State
FI_i	Follower Identity of Agent *i*	Individual	State
$WILT_i$	Weighted ILT based on observing Interactions	Individual	State
LP_{ij}	Leadership Perception of Agent *i* Towards Agent *j*	Dyadic	State

Table 2b

Stepwise Interactional Rules for Social Cognitive ABM

Stage 1: Initial Interaction Based on Leadership Schemas	
Step	Description
1	Interaction clock is set to 0; each agent is assigned all entity variables.
2	Two agents (*i* and *j)* are randomly selected for dyadic interaction.
3	Each agent decides to claim leadership based on her leader and follower self-schema. Specifically, if the agent's leader self-schema is greater than her follower self-schema, the agent will move to step 4. If it is not, the agent will not claim leadership.
4	Each agent uses her leader self-schema to determine whether to claim leadership. The higher the self-schema, the more likely the agent will claim.
5	If agent *j* claimed leadership, agent *i* evaluates agent *j* to determine if they will grant agent *j* 's claim. agent *i* then proceeds to step 6. If agent *j* did not claim, agent *i* does not grant.
6	Agent *i* compares her ILT to agent *j*'s leadership characteristics. The closer they are, the more likely agent *i* moves to step 7. Alternatively, agent *i* does not grant leadership.
7	Agent *i* uses her follower self-schema to determine if she will grant leadership. The higher the probability, the more likely she will grant leadership.
8	Steps 5 -7 repeats once for the Agent *j* evaluating agent *i.*
9	Agent *i and Agent j* each change their leader identity score (LI) from the previous iteration. They add .5 if they granted leadership, subtract .5 if they were not granted leadership, and nothing changes if they did not claim.
10	Agent *i and Agent j* each change their follower identity score (FI) from the previous iteration. They add .5 if they granted leadership, subtracts .5 of they did not grant leadership, and nothing changes if the other agent did not claim.
11	Agent *i and Agent j* each change their leadership perception (LP) score for each other from the previous iteration. If the agent granted leadership, they add 1 to their LP score for the other agent.
12	Every agent in the team internalizes the result of the double interact such that: for agents that receive a grant, her current ILT adjusts so that it is closer by 1 to that granted agents (i.e., 1- or +1) leadership characteristics. This becomes her new weighted ILT (wILT)
13	Each agent repeats Steps 2- 12 until they have had ten dyadic interactions *that they are involved in*. At this point, their contextualized leader identity and weighted ILT become solidified and are now used as her criteria for claiming/granting leadership. At this stage, the simulation proceeds to the next section.
Stage 2: Interaction Driven by Weighted ILT (After all agents have participated in ten interactions)	
Step	Description
1	Two agents (*i* and *j)* are randomly selected for dyadic interaction.
2	Each agent uses her contextualized leader identity to determine the probability that she will claim leadership; the agent then decides to claim or not claim leadership. The higher the LI, the more likely they claim.
3	The agent compares her weighted ILT to the other agent's leadership characteristics. The closer they are, the more likely she will grant leadership. If the other agent did not claim, they do not grant leadership.
4	Agent *i and Agent j* each change their leader identity score (LI) from the previous iteration. They add .5 if they granted leadership, subtract .5 if they were not granted leadership, and nothing changes if they did not claim.
5	Agent *i and Agent j* each change their follower identity score (FI) from the previous iteration. They add .5 if they granted leadership, subtracts .5 of they did not grant leadership, and nothing changes if the other agent did not claim.
6	Agent *i and Agent j* each change their leadership perception (LP) score for each other from the previous iteration. If the agent granted leadership, they add 1 to their LP score for the other agent.

Table 2c

Primary Simplifying Assumptions for Social Cognitive ABM

Assumption Type	**Simplifying Assumption**	**Conceptual Support**	**Citation(s)**
General	Dyadic interactions represent the core of leadership emergence	Double interacts are the clear unit of interactions across multiple works	DeRue & Ashford, 2010; DeRue, 2011
General	Individuals first determine self-decisions (i.e. should I claim) before evaluating others	Original works discuss self-decisions as foundational to the leadership process	Acton et al., 2019; DeRue, Ashford, & Cotton, 2009
Unique to Perspective	Leader/Follower identity starts at leader/follower self-schema	In its core conceptualization, self-schemas represent the foundation of identity	Lord & Chui, 2018; Lord, Gatti, & Chiu, 2016
Unique to Perspective	Both self-schema comparison and overall leader self-schema drive identity	The self-schema comparison is the driver of claiming behavior, but the extent to which the person is schematic on leadership also matters	Acton et al., 2019; Lord, Gatti, & Chiu, 2016; Markus & Wurf, 1987
Unique to Perspective	Both ILT other characteristic comparisons, as well as the follower self-schema, drive granting behavior	For grants, individuals primarily compare their dyadic partners characteristics to their ILT but the extent to which the person is schematic on followership also matters	Epitropaki et al., 2017; Lord & Brown, 2003
Unique to Perspective	Individuals adjust both their leader and follower identities based upon the role of followers in dyadic interactions. If a person does not attempt leadership, identities do not change	The social cognitive perspective argues that the leadership identity process is driven by the *follower* perception of a leader action	Lord & Chui, 2018; Lord & Maher, 2002
Unique to Perspective	Individuals leadership perception of others is increased from the other persons congruence with their implicit leadership theory	The social cognitive perspective argues that changes in perception are fully attributed to the ILT comparison process	Shondrick, Dinh, & Lord (2010); Dinh & Lord (2012)

Table 2d

Core Model Initializing Parameters for Social Cognitive ABM

Parameter	**Description**	**Parameter Level**	**Starting Value(s)**
ILTi	Implicit Leadership Theory	Agent	Range = 42 – 90
Ci	Prototypical Leadership Characteristics	Agent	Range = 10 – 90
LSSi	Leader Self Schema	Agent	Range = 27.10 – 90
FSSi	Follower Self Schema	Agent	Range = 28.18 – 90
Interaction Cutoff	How many interactions before rules change to Stage two	Environment	10
Leader Identity	Contextualized Leader Identity	Agent	LSSi
Follower Identity	Contextualized Follower Identity	Agent	FSSi

Table 2e

Formal Predictions Tested in Social Cognitive ABM

Hypothesis #	Hypothesis
2a	*If an individual is more schematic on leadership than followership, then that individual will be more likely to be seen as a leader.*
2b	*If teams have individuals who are more schematic on leadership and followership, then they will have a more shared leadership structure.*
2c	*If teams have individuals with smaller differences in ILT-other comparisons across dyads, then they will have a more shared leadership structure.*
2d	*If teams have a smaller difference in ILT across individuals, then they will more quickly reach a collective leadership structure.*
2e	*If teams have smaller differences in leader self-schema/follower self-schema comparisons within dyads, then they will more quickly reach a collective leadership structure.*
2f	*Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.*
2g	*Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.*
2h	*Across time, an individual's leadership rank will become more consistent.*

Table 3

Parameter Sensitivity Testing Plan

Model	Unique Element at Stage 1	Unique Interactional Process at Stage 2
Base Model	ILT-Self Comparison	ILT-Other Comparison
Social Interactionist	Leadership Structure Schemas	Contextualized Leader and Follower Identity
Social Cognitive	Leader/Follower Self-Schemas	Weighting of ILT Leader Identity
Mode of Assessment	*Variance Accounted for in Outcomes*	*Assessment of Leadership Emergence Trajectories*

Table 4a

Descriptive Statistics for Individual Level Variables (SI Perspective)

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Leadership Structure Schema	1.50	0.50							
2. Self-Prototypical ILT Characteristics	64.73	13.60	-.02 [-.06, .01]						
3. ILT (Prototypical)	72.04	9.55	-.01 [-.05, .02]	.20** [.16, .23]					
4. ILT- Self Characteristic Difference (Prototypical)	13.28	10.13	.02 [-.02, .05]	-.53** [-.56, -.50]	.22** [.19, .26]				
5. Follower Identity	87.03	24.87	.23** [.20, .27]	-.04* [-.08, -.01]	.00 [-.03, .04]	.04* [.00, .07]			
6. Leader Identity	83.21	30.95	-.01 [-.05, .03]	.47** [.44, .49]	-.14** [-.17, -.10]	-.72** [-.74, -.70]	.14** [.11, .18]		
7. Leader Score	4.71	1.17	-.00 [-.04, .03]	.46** [.43, .49]	-.13** [-.17, -.10]	-.75** [-.76, -.73]	.23** [.20, .27]	.88** [.87, .88]	
8. Follower Score	4.71	1.01	.32** [.29, .35]	-.05** [-.08, -.01]	-.01 [-.05, .02]	.05* [.01, .08]	.83** [.82, .85]	.14** [.10, .17]	.31** [.28, .34]

Notes. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. Values at Time 500. *N = 3000 (people).* LSS = Leadership Structure Schema (0 = Hierarchical, 1 = Shared). Self-ILT = Personal standing on prototypical ILT traits. ILT = Implicit Leadership Theory of prototypical traits.

Table 4b

Descriptive Statistics for Team Level Variables (SI Perspective)

Variable	*M*	*SD*	1	2	3	4	5	6
1. ILT-Self characteristic Difference	13.28	3.95						
2. ILT-Other Difference	14.45	3.54	.67** [.62, .72]					
3. Proportion of Shared LSS	.50	.20	.06 [-.02, .15]	.04 [-.05, .12]				
4. Leadership Incoming Rating Agreement	.42	.19	.58** [.52, .63]	.44** [.37, .51]	-.05 [-.14, .03]			
5. Leadership Outgoing Rating Agreement	.25	.13	.14** [.05, .22]	.12** [.03, .21]	-.18** [-.27, -.10]	-.17** [-.26, -.08]		
6. Leadership Density	28.24	4.69	-.77** [-.81, -.73]	-.60** [-.65, -.54]	.30** [.22, .38]	-.59** [-.65, -.53]	-.29** [-.37, -.21]	
7. Leadership Centralization	.22	.10	.69** [.64, .73]	.53** [.47, .59]	-.19** [-.27, -.10]	.71** [.67, .75]	.14** [.05, .22]	-.84** [-.87, -.82]

Notes. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. Values at Time 500. *N = 500 (teams).* * indicates $p < .05$. ** indicates $p < .01$. ILT-self characteristic difference = Average team difference between each person's ILT-self characteristic comparison. ILT-Other Difference = Average team difference between each person's and the person's dyadic interaction partner's characteristics.

Table 5a

Descriptive Statistics for Individual Level Variables (SC Perspective)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Leader Self-Schema	70.24	12.34									
2. Follower Self-Schema	67.82	11.52	.35** [.32, .38]								
3. Self-Prototypical ILT Characteristics	64.73	13.60	.01 [-.02, .05]	.03 [-.00, .07]							
4. ILT (Prototypical)	72.04	9.55	.02 [-.02, .05]	.00 [-.03, .04]	.20** [.16, .23]						
5. ILT- Self Characteristic Difference	13.28	10.13	-.01 [-.04, .03]	-.04* [-.07, -.00]	-.53** [-.56, -.50]	.22** [.19, .26]					
6. ILT-Other Characteristic Difference	14.20	10.71	.03 [-.01, .06]	.01 [-.03, .04]	.05** [.01, .09]	.24** [.21, .28]	.08** [.05, .12]				
7. Follower Identity	95.48	6.35	.17** [.14, .21]	.52** [.49, .55]	-.02 [-.06, .01]	.02 [-.02, .06]	.00 [-.03, .04]	-.08** [-.12, -.05]			
8. Leader Identity	90.15	15.28	.41** [.38, .44]	.16** [.12, .19]	.23** [.20, .27]	.02 [-.02, .06]	-.37** [-.40, -.33]	-.03 [-.07, .00]	.06** [.02, .09]		
9. Leader score	4.27	1.45	.45** [.42, .48]	.13** [.09, .16]	.22** [.18, .25]	.00 [-.03, .04]	-.38** [-.41, -.35]	-.04* [-.07, -.00]	.04* [.01, .08]	.86** [.85, .86]	
10. Follower Score	4.27	.67	-.01 [-.05, .02]	.01 [-.02, .05]	-.05** [-.09, -.02]	-.01 [-.04, .03]	.01 [-.02, .05]	-.17** [-.20, -.13]	.47** [.44, .50]	-.03 [-.06, .01]	.02 [-.02, .05]

Notes. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. Values at Time 500. *N = 3000 (people).* * indicates $p < .05$. ** indicates $p < .01$.

Table 5b

Descriptive Statistics for Team Level Variables (SC Perspective)

Variable	*M*	*SD*	1	2	3	4	5	6
1. L/F Self-Schema Dyadic Difference	13.78	3.12						
2. ILT-Other Dyadic Difference	44.91	27.07	-.02					
			[-.11, .07]					
3. ILT (Prototypical) Variance	75.93	44.34	-.06	.40**				
			[-.15, .03]	[.32, .47]				
4. Leadership Incoming Rating Agreement	.67	.17	.11*	.37**	.02			
			[.02, .19]	[.29, .44]	[-.07, .11]			
5. Leadership Outgoing Rating Agreement	.08	.05	-.02	-.16**	-.06	-.47**		
			[-.10, .07]	[-.24, -.07]	[-.15, .03]	[-.54, -.40]		
6. Leadership Density	25.64	3.12	-.09*	-.45**	.00	-.61**	.20**	
			[-.17, -.00]	[-.52, -.38]	[-.09, .09]	[-.67, -.56]	[.12, .29]	
7. Leadership Centralization	.33	.10	.10*	.40**	.04	.75**	-.36**	-.80**
			[.02, .19]	[.32, .47]	[-.05, .13]	[.71, .79]	[-.43, -.28]	[-.83, -.77]

Notes. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. Values at Time 500. *N = 500 (teams).* * indicates $p < .05$. ** indicates $p < .01$.

Table 6

Correlations in Individual Leadership Rank Across Time

Variable	1	2	3	4
1. Time 0 Leadership Rank				
2. Time 10 Leadership Rank	**.73****			
3. Time 20 Leadership Rank	.65**	**.88****		
4. Time 30 Leadership Rank	.62**	.83**	**.92****	
5. Time 40 Leadership Rank	.58**	.79**	.88**	**.94****

Note. Leadership Rank represents the relative standing of each person's leader score compared to the other team members (1 = Lowest Rank, 6 = Highest Rank). Diagonal represents correlation with a previous time point. * indicates $p < .05$. ** indicates $p < .01$.

Table 7a

Regression Based Sensitivity Analysis for Social Interactionist Model

Model Outcome	Predictor	*b*	*beta*	*sr2*	*r*	Fit
Density	(Intercept)	3.30**				
	LSS Prop	1.03**	.24	.06	.24**	
						R^2 = .06**
Centralization	(Intercept)	.39**				
	LSS Prop	.03	.05	.00	.05	
						R^2 = .00
Leadership Rating Agreement	(Intercept)	.23**				
	LSS Prop	.15**	.24	.06	.24**	
						R^2 = .06**

Notes. A significant b-weight indicates the beta-weight and semi-partial correlation are also significant. b represents unstandardized regression weights. beta indicates the standardized regression weights. sr2 represents the semi-partial correlation squared. r represents the zero-order correlation. * indicates p < .05. ** indicates p < .01. LSS Prop= Proportion of Individuals with Shared Leadership Structure Schemas on the Team.

Table 7b

Regression Based Sensitivity Analysis for Social Cognitive Model

Model Outcome	Predictor	*b*	*beta*	*sr2*	*r*	Fit
Density	(Intercept)	-1.31**				
	LSS M	.09**	.70	.43	.59**	
	LSS V	.00	.05	.00	.02	
	FSS M	-.05**	-.32	.09	-.08	
	FSS V	-.00**	-.09	.01	-.07	
						R^2 = .45**
Centralization	(Intercept)	.91**				
	LSS M	-.02**	-.51	.23	-.39**	
	LSS V	.00	.00	.00	.02	
	FSS M	.01**	.36	.11	.18**	
	FSS V	.00	.05	.00	.03	
						R^2 = .26**
Leadership Rating Agreement	(Intercept)	.33**				
	LSS M	-.01**	-.24	.05	-.14**	
	LSS V	.00	.07	.00	.07	
	FSS M	.01**	.31	.09	.24**	
	FSS V	-.00	-.04	.00	-.06	
						R^2 = .12**

Notes. A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *beta* indicates the standardized regression weights. *sr2* represents the semi-partial correlation squared. *r* represents the zero-order correlation. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. * indicates $p < .05$. ** indicates $p < .01$. LSS = Leader Self-Schema. FSS = Follower Self-Schema. M = Mean. V = Variance.

Table 8

Summary of Results from Hypothesis Testing

#	Perspective	Hypothesis	Support?	Effect size
1A	Social Interactionist	If an individual has a Hierarchical LSS, then that person will be perceived more as a leader.	Yes	Low
1B	Social Interactionist	If an individual has a Shared LSS, then that person will perform more of a follower role.	Yes	Low
1C	Social Interactionist	If teams have a greater proportion of individuals with shared leadership structure schemas, then they will have a more shared leadership structure.	Yes	Low
1D	Social Interactionist	If teams have smaller average differences in individual-level, ILT-to-self comparisons, then they will have a more shared leadership structure.	Yes	High
1E	Social Interactionist	If teams have smaller differences in ILT-other comparisons within dyads, then they will have a more shared leadership structure.	Yes	Medium
1F	Social Interactionist	Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.	Yes	Medium
1G	Social Interactionist	Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.	Yes	High
2A	Social Cognitive	If an individual is more schematic on leadership than followership, then that individual will be seen more as a leader.	Yes	Low
2B	Social Cognitive	If teams have individuals who are more schematic on leadership and followership, then they will have a more shared leadership structure.	Partial	Medium
2C	Social Cognitive	If teams have individuals with smaller differences in ILT-other comparisons across dyads, then they will have a more shared leadership structure.	Yes	Medium
2D	Social Cognitive	If teams have a smaller difference in ILT across individuals, then they will more quickly reach a collective leadership structure.	No	n/a
2E	Social Cognitive	If teams have smaller differences in leader self-schema/follower self-schema comparisons within dyads, then they will more quickly reach a collective leadership structure.	No	n/a
2F	Social Cognitive	Across time, from each dyadic interaction, team members' contextualized leader identities will become more stable.	Yes	Medium
2G	Social Cognitive	Across time, from each dyadic interaction, team members' contextualized follower identities will become more stable.	Yes	High
2H	Social Cognitive	Across time, an individual's leadership rank will become more consistent.	Yes	High

Note. Hypothesis 2B had large support for leader-self schema and no support for follower self-schema.

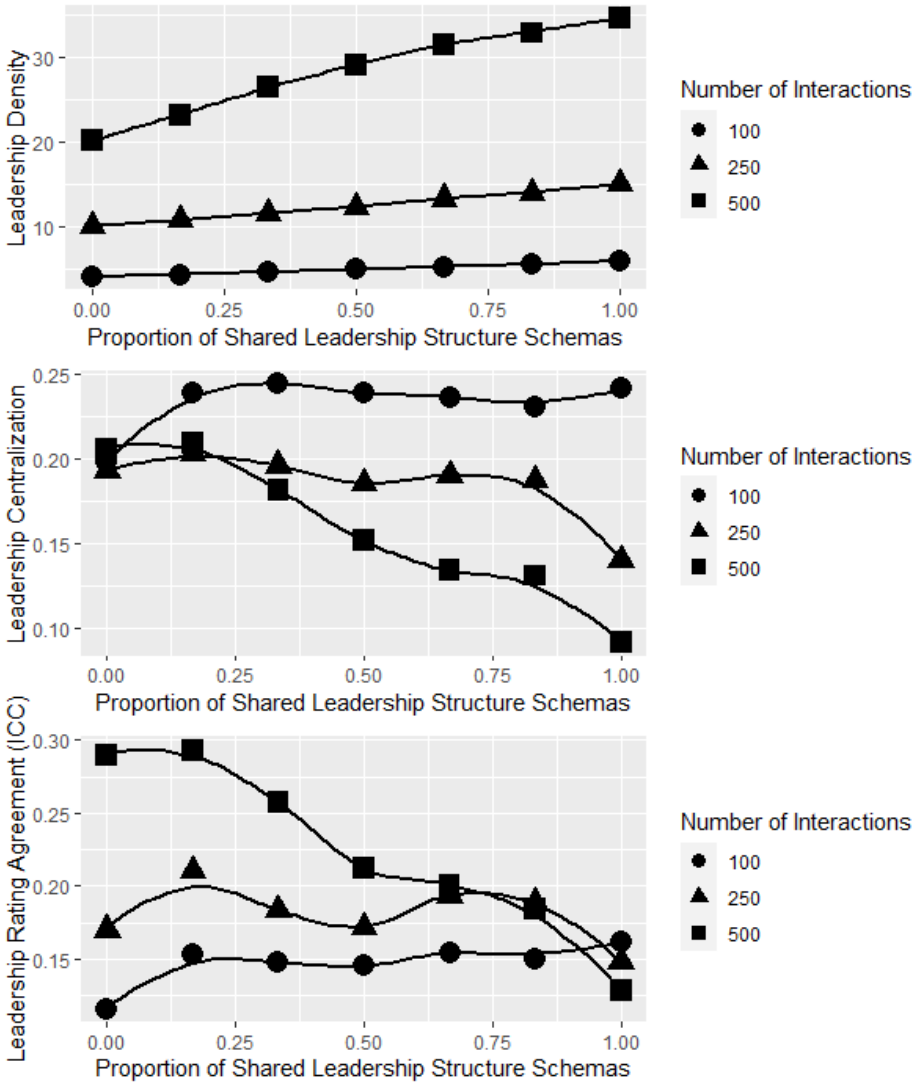

Figure 1. Dependent Variables Plotted Across Different Proportions of LSS.

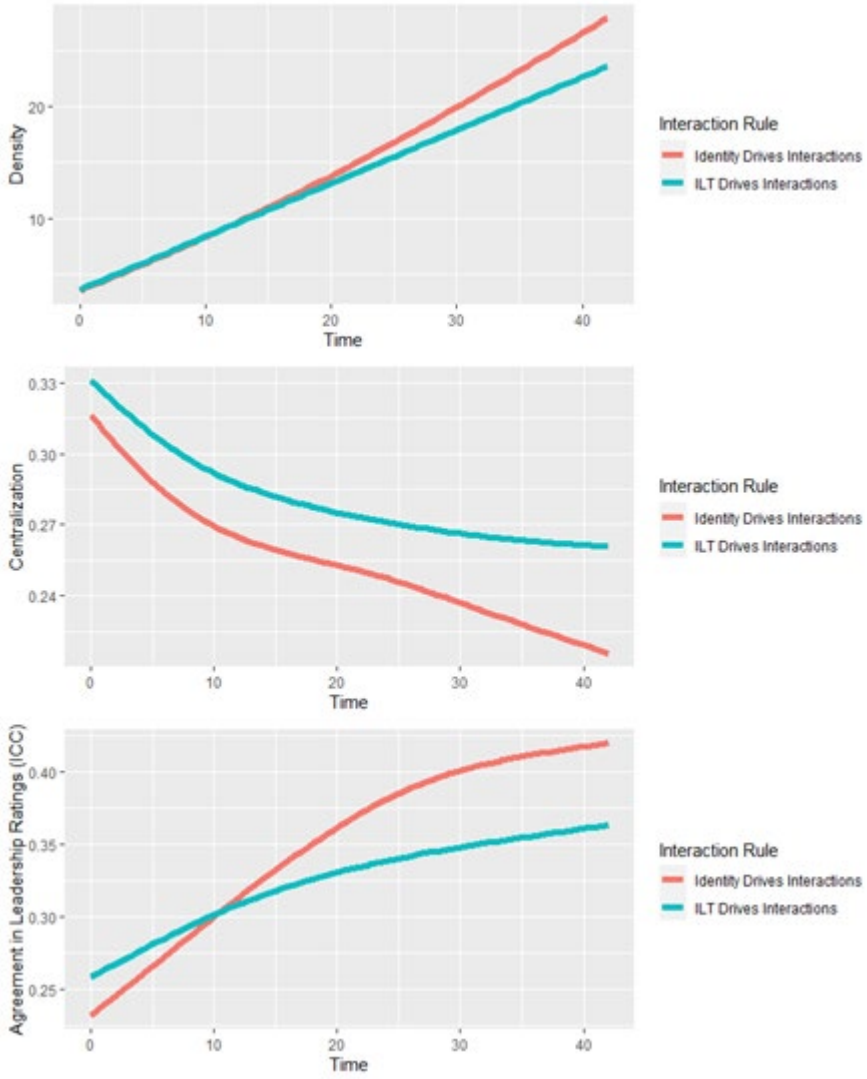

Figure 2. Dependent Variable Comparison Across Interactional Rules for SIP.

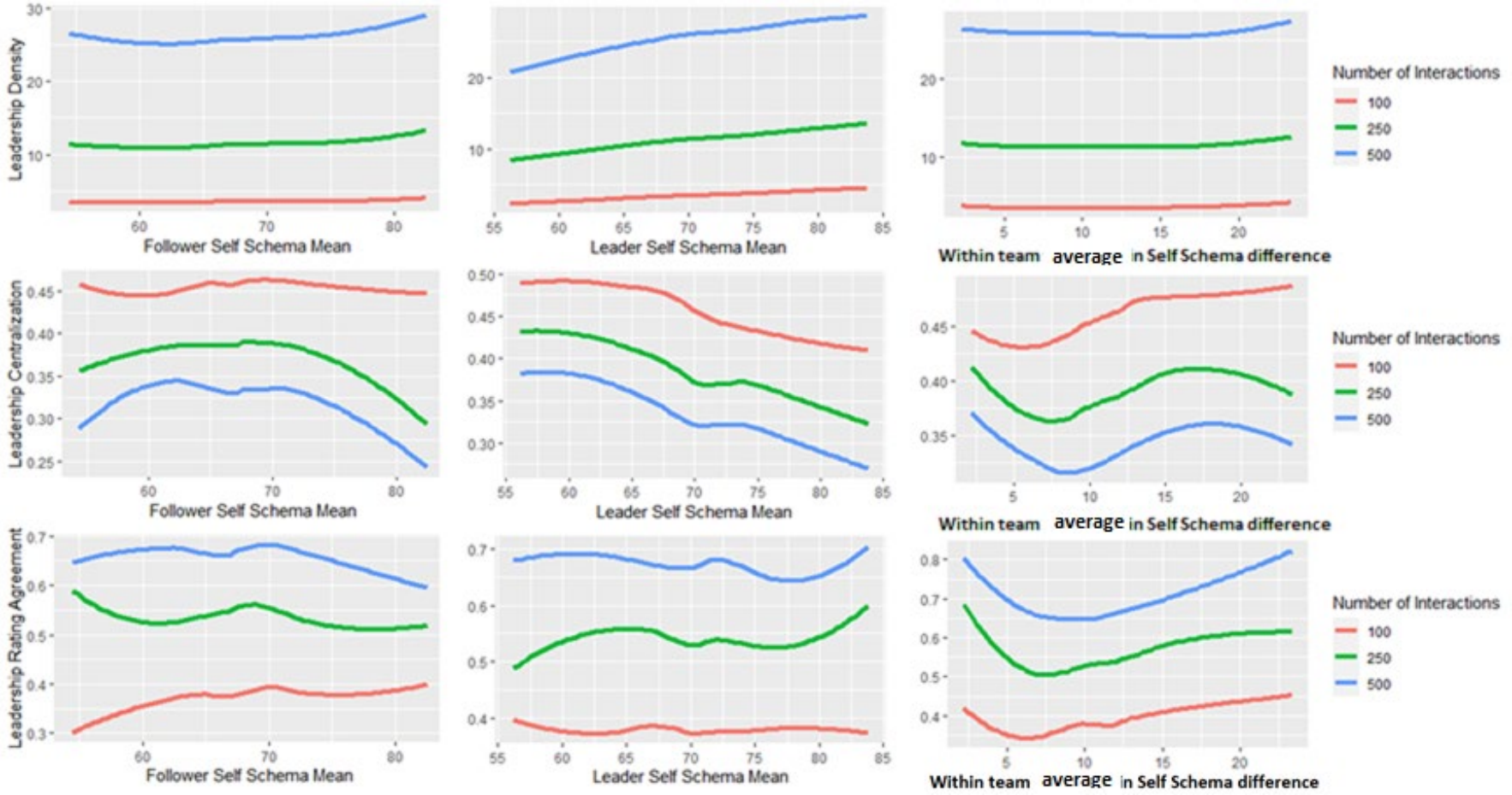

Figure 3. Dependent Variables Plotted Across Self-Schema Variables (Averages).

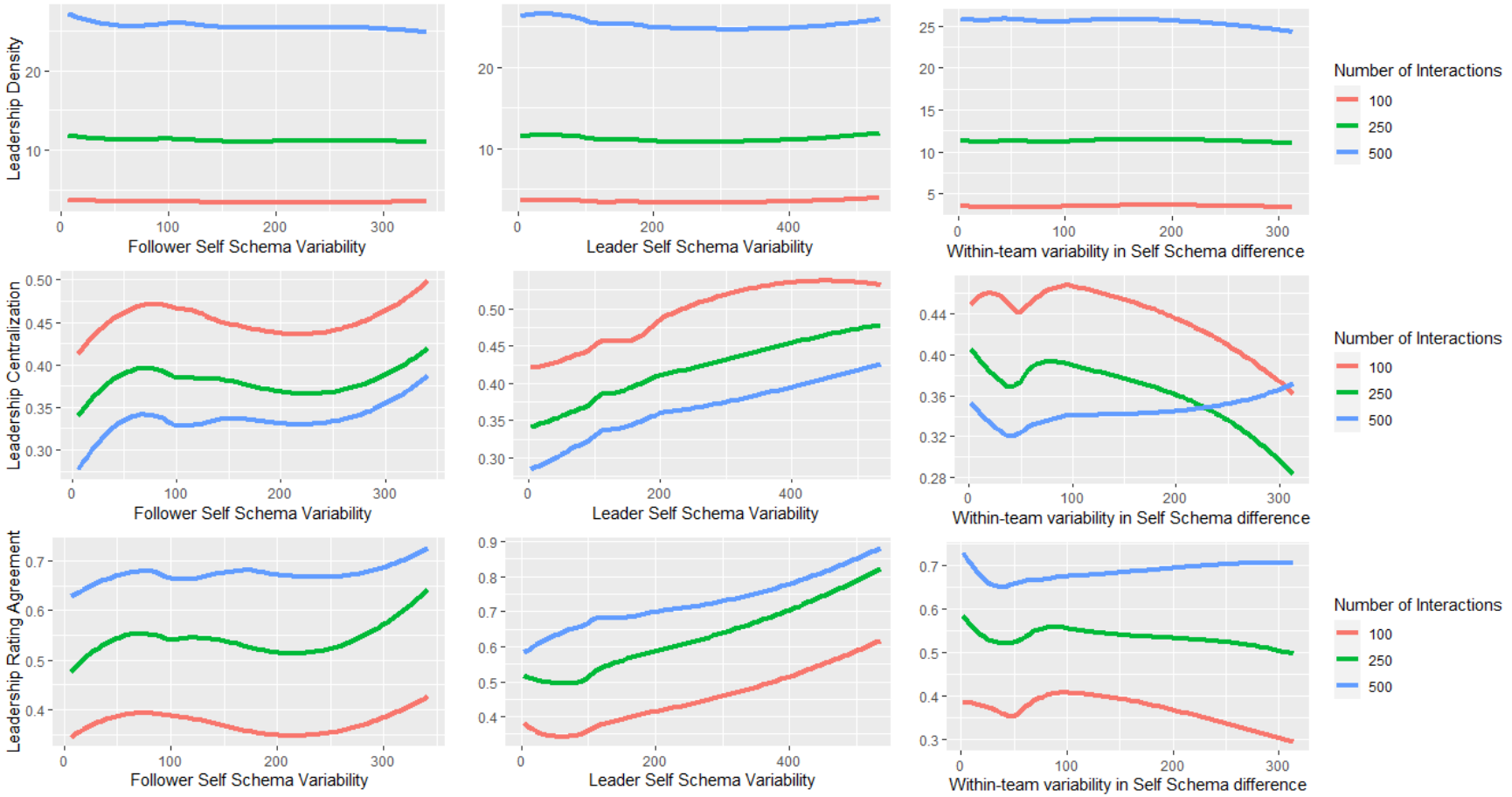

Figure 4. Dependent Variables Plotted Across Self-Schema Variables (Variability).

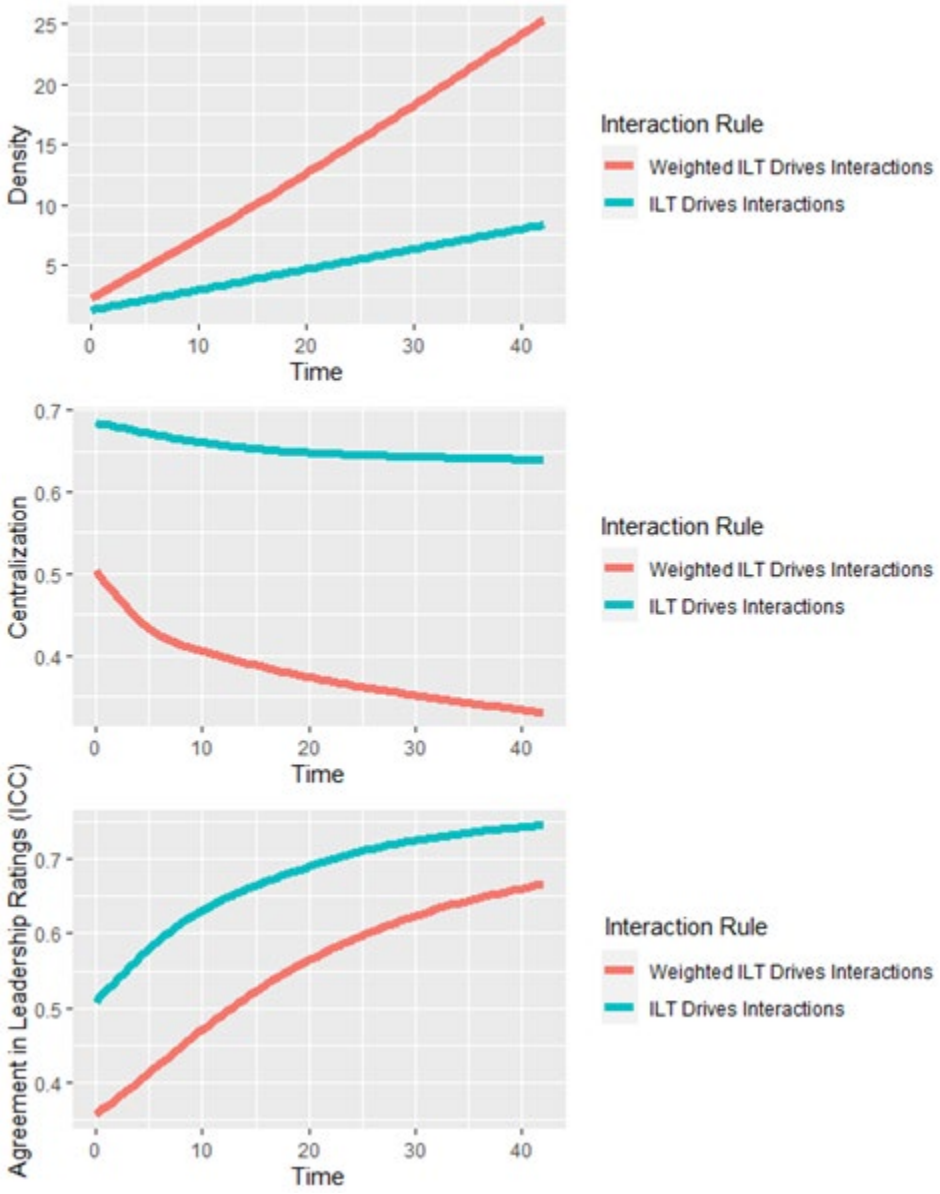

Figure 5. Dependent Variable Comparison Across Interactional Rules for SCP.

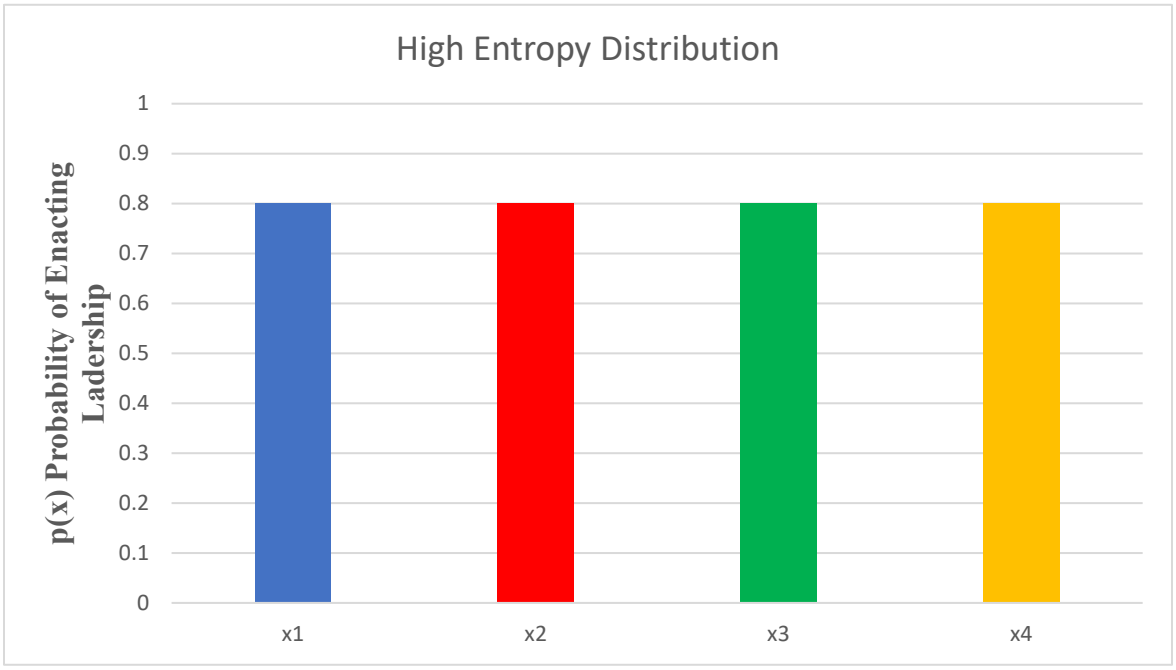

Figure 6. Representation of Collective Leadership Using Entropy Perspective.

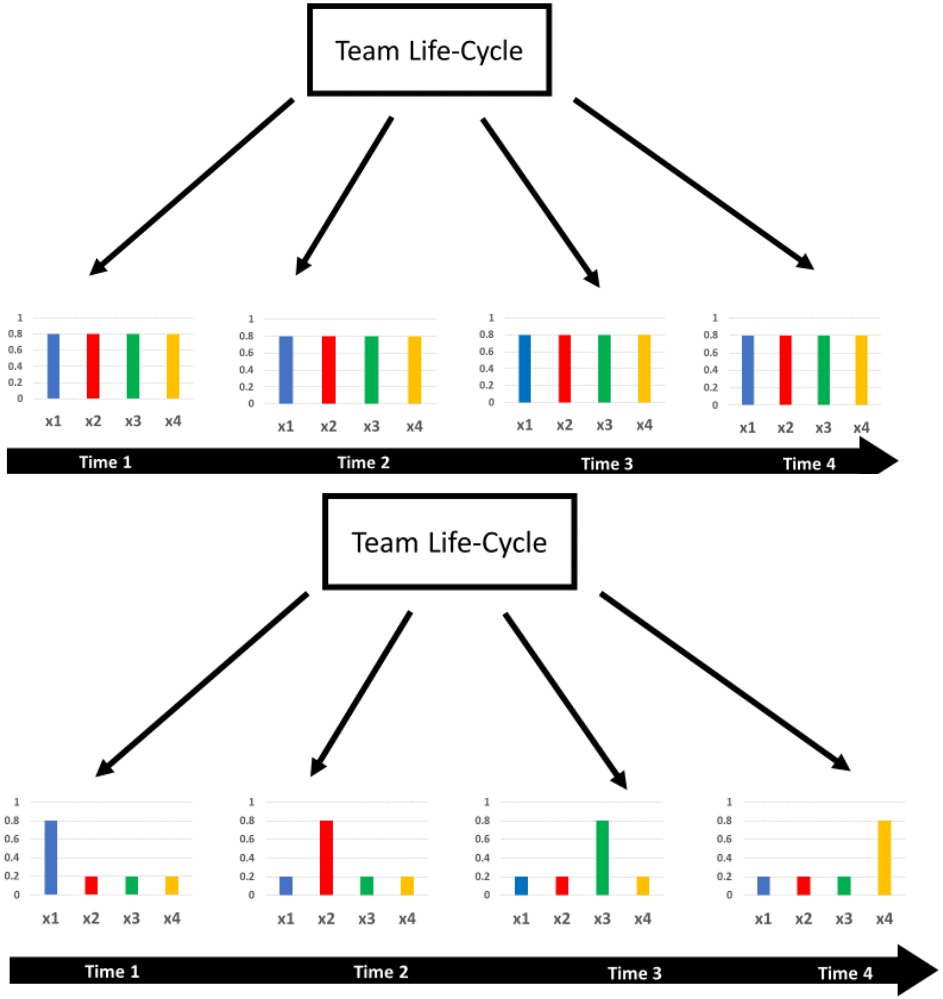

Figure 7. Two Forms of Shared Leadership.

Notes. The top figure represents a form of shared leadership that has not emerged to a collective entity. The lower figure represents a form of shared leadership that has emerged to a collective entity. x represents one person on the team.