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Graig Michael Chow

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SOCIAL INTERACTION AND COLLECTIVE EFFICACY DISPERSION: A SOCIAL NETWORK ANALYSIS

By

Graig Michael Chow

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ABSTRACT

SOCIAL INTERACTION AND COLLECTIVE EFFICACY DISPERSION:
A SOCIAL NETWORK ANALYSIS

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The purpose of this study was to investigate the influence of social interaction on collective efficacy dispersion, and to examine the moderating influence of dispersion on team-related outcomes. The sample consisted of 46 intercollegiate women's softball teams. A longitudinal design was employed with two time points: beginning of the season and middle of the season. At Time 1, participants completed demographic, collective efficacy, and team commitment questionnaires. At Time 2, participants completed demographic, collective efficacy, team commitment, and sociometric questionnaires. Based on the sociometric data, group-level social network metrics were calculated and cohesive subgroups were identified within teams using Klique Finder (Frank, 1995). A series of hypotheses were made regarding the influence of social network variables on collective efficacy dispersion and the moderating influence of collective efficacy dispersion on team performance and commitment. The majority of teams in the study did not demonstrate evidence of subgroups with only 33% having communication subgroups and 28% having friendship subgroups. Membership in cohesive subgroups was related to number of years on the team and to a lesser degree, starting status and collective efficacy beliefs. Results demonstrated that teams with communication subgroups had more collective efficacy dispersion than teams without communication subgroups. However, there was a lack of support regarding the influence of subgroup's prior mean levels of collective efficacy on collective efficacy

beliefs at Time 2, indicating that individuals' collective efficacy beliefs were not influenced by members of their subgroup. Centralization of the communication network emerged as a positive predictor of collective efficacy dispersion. Teams with more centralized communication ties had higher levels of dispersion than team with less centralized communication ties. Limited support was found for collective efficacy dispersion as a predictor and moderator. Collective efficacy dispersion at the middle of the season was negatively related to run differential at the end of the season, and collective efficacy dispersion moderated the relationship between aggregated collective efficacy and run differential.

DEDICATION

To my mom, Lissa, for always believing in me and to Leena
for all of her love and many sacrifices.

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CHAPTER 1

INTRODUCTION

Nature of the Problem

The nature of intact teams involves members performing together in dynamic and complex environments where individuals develop beliefs about the team that may be similar or different from their teammates. While shared experiences provide a common frame of reference that draws team members' beliefs closer together, the importance given to the structure of group interaction is often overlooked. Depending on the structure of interpersonal interaction, group members' beliefs may converge or diverge over time creating dispersion at the team level, which has implications for team functioning, performance, and affective states.

The purpose of this dissertation was to examine the emergence of collective efficacy dispersion and to investigate the team-related consequences of collective efficacy dispersion. This chapter begins with a brief review of the collective efficacy research, discusses the concept of collective efficacy dispersion, introduces social network analysis as a tool for examining interpersonal interaction and social influence, and concludes with a discussion of the tenets and limitations.

Collective efficacy is "a group's shared belief in their conjoint capabilities to organize and execute the courses of action required to produce given levels of attainments" (Bandura, 1997, p. 476). Theorists have asserted that collective efficacy is an important determinant of team performance (Bandura, 1997; Gist, 1987; Lindsley, Brass, & Thomas, 1995; Zaccaro, Blair, Peterson, & Zazanis, 1995). Judgments of collective efficacy influence the tasks that teams select to engage in, the amount of effort members put forth together, the degree to which members persevere and remain task-oriented when the team is struggling, and the level of resiliency to bounce back from wrenching defeats (Bandura, 1997). Empirical research in sport and organizational psychology has provided support for the performance-oriented consequences of collective efficacy beliefs. Teams with a stronger sense of collective efficacy outperform teams with a weaker sense of collective efficacy across various group environments including sport (Feltz & Lirgg, 1998), executive training (Gibson, Randel, & Earley, 2000), health (Gibson, 1999), financial organizations (Campion, Medsker, & Higgs, 1993), academics (Parker, 1994), and military units (Chen, Webber, Bliese, Mathieu, Payne, Born, & Zaccaro, 2002). A meta-analysis of 53 studies found that collective efficacy was positively related to team performance with a corrected mean correlation of .41 (Gully, Incalcaterra, Joshi, & Beaubien, 2002).

How teams develop their sense of collective efficacy is somewhat similar to how self-efficacy beliefs are formed, that is through sources of efficacy information. Because perceptions of collective efficacy are rooted in perceptions of self-efficacy, the sources of efficacy beliefs are hypothesized to be isomorphic across levels (Bandura, 1997; Lindsley et al., 1995). Based on the tenets of self-efficacy theory (Bandura, 1977, 1997), researchers have investigated sources of collective efficacy by extending the antecedents of personal efficacy to the group level. Consistent with self-efficacy theory, studies have found that collective efficacy beliefs are influenced by previous team performance (Feltz & Lirgg, 1998), vicarious experience (Chase, Feltz, & Lirgg, 2003), verbal persuasion (Hodges & Carron, 1992), and physiological/emotional states (Greenlees, Nunn, Graydon, & Maynard, 1999). However, collective efficacy is not a mere extension of self-efficacy theory. While there are similarities between the antecedents of self- and collective efficacy beliefs, the assumption of homology may be inaccurate (Chen & Bliese, 2002; Chen et al., 2002). Consequently, researchers have identified antecedents that are unique to collective efficacy such as group cohesion (Paskevich, Brawley, Dorsch, & Widmeyer, 1999), leadership (Watson, Chemers, & Preiser, 2001), and motivational climate (Magyar, Feltz, & Simpson, 2004).

Although collective efficacy is conceptualized as a group level attribute, the construct is measured at the individual level. A team level estimate is derived by aggregating group members' individual perceptions of collective efficacy. In order to justify aggregating individual perceptions of collective efficacy to form the higher level construct (i.e., shared collective efficacy), researchers calculate the degree of within-team variability in members' responses. If a relatively high level of within-team agreement is demonstrated, collective efficacy is considered a shared group level phenomenon which provides justification for aggregating the lower level responses. However, if members' perceptions of collective efficacy demonstrate insufficient levels of consensus, some researchers contend that the construct is operating at the individual level (Gibson, 1999; Gully et al., 2002) or that there is no distinguishable collective efficacy for the team as a whole (Bandura, 1997). In contrast, Moritz and Watson (1998) argue that focusing only on shared collective efficacy beliefs disregards within-team variability, which may provide insight into team functioning and performance. For instance, a team with relatively high collective efficacy (i.e., group mean) may be comprised of members who hold different beliefs pertaining to the team's capabilities. These within-team differences in collective efficacy may contribute to conflict among members, a lack of cohesiveness, and varying amounts of effort exhibited by certain members.

The absence of perceptual consensus does not imply that a reasonable estimate of collective efficacy does not exist (Myers & Feltz, 2007), just as a substantial degree of consensus within teams does not imply that there is a total lack of within-team variability. In fact, complete unanimity of group members' collective efficacy beliefs is rare (Bandura, 1997). Individuals occupying different positions or serving different functions within the same social system may differ in their sense of collective competence (Bandura, 1993). For instance, a veteran player who has experienced constant failure throughout her tenure may possess very different beliefs about the team's functioning than a first-year player who has had few opportunities to perform collectively with her teammates. When individual perceptions of collective efficacy are aggregated to the group level, these differences are discarded and within-team variability is treated as constant across all teams that achieve a sufficient level of consensus. However, teams with similar aggregated collective efficacy beliefs may have different levels of within-group variation (see Figure 1). Furthermore, differences in group members' collective efficacy beliefs at the individual level create dispersion at the team level, and current theory does not address how these differences affect motivational and behavioral consequences.

A dispersion theory moves beyond the dichotomous view of perceptual consensus and conceptualizes within-team variability as a focal unit level variable (Brown, Kozlowski, & Hattrup, 1996; Chan, 1998). That is, rather than being used as a statistical prerequisite for aggregation, dispersion theories posit that the variance lost during aggregation procedures may be of substantive interest. Thus, the degree of within-group variation can be investigated as an independent variable, moderating variable, or dependent variable (Brown et al., 1996; Chan, 1998). Collective efficacy represents a useful theoretical construct in which to examine dispersion as a focal variable because it is characterized by a representative value of members' perceptions and the variability around that central belief (Bandura, 1997). A dispersion theory of collective efficacy assumes that within-team variation in group members' beliefs is as meaningful as the central tendency around that belief.

While conceptual arguments for investigating collective efficacy dispersion as a focal variable have been presented in the literature (Chan, 1998; DeRue, Hollenbeck, Ilgen, & Feltz, in press; Moritz & Watson, 1998), only one empirical study has investigated this topic. Arthur, Bell, and Edwards (2007) examined the degree of within-team variability in efficacy beliefs with dyadic teams performing a perceptual-motor skill task that involved information processing and was highly interdependent. The purpose of this study was to examine the moderating influence of collective efficacy dispersion on the aggregated collective efficacy-team performance relationship. They found that the relationship between aggregated collective efficacy and team performance was stronger for dyads with higher levels of perceptual consensus than for dyads with lower levels of consensus. Further, dyads with shared collective efficacy beliefs outperformed dyads with dispersed collective efficacy beliefs, regardless of the magnitude of collective efficacy. This study represents an important shift in the conceptualization of collective efficacy and provides preliminary support for the usefulness of collective efficacy dispersion as a focal variable in team research.

Statement of the Problem

The overemphasis of collective efficacy as a shared belief has contributed to a lack of understanding regarding the emergence of collective efficacy. Thus, little is known about why some teams develop more interrelated beliefs, while other teams develop more dispersed beliefs. Theorists have assumed that common experiences such as outcomes of team performance are sufficient for creating shared collective efficacy beliefs. This perspective is limited however, because it assumes that teams that have received performance feedback always achieve the same level of perceptual consensus, and it fails to adequately explain why teams with similar experiences attain different levels of dispersion. Another perspective suggests that substantial social interaction is a necessary precondition for the development of shared collective efficacy beliefs (Jung & Sosik, 2003), though the role of group interaction in the formation of collective efficacy has largely been ignored. Gibson (1999) proposed that collective efficacy develops "as group members collectively acquire, store, manipulate, and exchange information about each other and about their task, context, process, and prior performance" (p. 138). Consistent with this observation, the current study examines social interaction as the foundation for consensus formation within teams. High levels of social interaction foster similarity among group members and promote the emergence of shared beliefs (Klein, Conn, Smith, & Sorra, 2001; Gonzalez-Roma, Peiro, & Tordera, 2002), whereas a lack of group interaction constrains information flow and produces dispersed beliefs.

A social network perspective is concerned with the structure or pattern of social relations between individuals and assumes that group interactions will explain outcomes at multiple levels of analysis beyond the attributes of individuals (e.g., experience, number of years on the team) or organizational context (Wasserman & Faust, 1994). Housed within social network analysis, network theories of social influence suggest that social interaction provides a conduit along which social influence or contagion flows. Lindsley et al. (1995) observed the social effects of collective efficacy and have argued that a shared sense of collective efficacy emerges as individuals interact and compare themselves with others to test and confirm their own perceptions. According to network theorists, social influence is a function of two independent processes – communication exchanges and interpersonal comparison based on friendship. Communication ties reflect instrumental interactions or task-related exchanges where information provides a mechanism of social influence. Information exchanges are likely to produce efficacy contagion as group members share and discuss aspects of team functioning such as strengths and weaknesses of the team, previous performances and goals. Social comparison reflects expressive interaction or affective relationships where similarity and closeness provide a pathway of influence. Comparison is similar to social modeling and is likely to produce contagion when individuals modify their collective efficacy beliefs to be consistent with others with whom they are affectively close. The social effects of communication and social comparison are captured by verbal persuasion and vicarious experience, respectively, in efficacy theory (Bandura, 1997).

An advantage of social network analysis is that group level metrics can be calculated that describe different features of a network's interaction structure. Perhaps the most common index of network structure used to compare different networks is structural density (Scott, 2000). Density is a measure of social proximity and refers to the proportion of ties in a network relative to the total number of possible ties in a network (Scott, 2000; Wasserman & Faust, 1994). Networks can be characterized as either dense or sparse depending on the density metric. Figure 2 illustrates a dense network on the left and a sparse network on the right. Communication network density reflects the extent to which actors share task-related information, while friendship network density reflects the extent to which actors are involved in personal relationships. Teams with densely configured instrumental and expressive ties outperform and are more committed to staying together than teams with sparsely configured ties (Balkundi & Harrison, 2006). In addition, density facilitates social diffusion and comparison processes which promote the emergence of shared beliefs in teams (Zohar & Tenne-Gazit, 2008).

While density quantifies the average of actor tendencies, centralization is a measure of variability or spread of social ties and reflects the extent to which a network revolves around a single central actor (Wasserman & Faust, 1994). Based on the centralization metric, networks can be characterized as centralized or decentralized. Figure 3 presents a centralized network on the left compared to a decentralized network on the right. In a centralized communication network, a central actor acquires information pertaining to the beliefs of all other members, while peripheral members are starved for information because they have limited interaction with each other. As centralization declines however, group members become equally central in the interaction structure and information flows more uniformly throughout the system. Consequently, decentralized communication networks are beneficial for complex tasks (Cummings & Cross, 2003; Sparrowe, Liden, Wayne, & Kraimer, 2001) and provide better opportunities for consensus formation (Zohar & Tenne-Gazit, 2008). Whereas centralized communication networks hinder social influence processes, centralized friendship structures promote interpersonal influence and the emergence of shared beliefs. Friendship centralization reflects the extent to which a central actor is involved in the majority of personal relationships and is based on affective visibility where the central actor provides a common frame of reference for interpreting the situation (Zohar & Tenne-Gazit, 2008). Group members who are engaged in a dyadic comparison process to few others tend to hold similar perceptions because they agree with the same significant other (Zohar & Tenne-Gazit, 2008). Accordingly, centralized communication networks are likely to produce higher levels of collective efficacy dispersion, while centralized friendship structures are likely to promote similar collective efficacy beliefs within teams.

Another way of characterizing a network is by determining whether subgroups are present within a team. In contrast to research that investigates subgroups based on demographic attributes (Lau & Murnighan, 1998), a social network approach examines subgroups according to patterns of social interaction. Thus, subgroups represent non-overlapping cohesive clusters and are defined in terms of a concentration of interactions within subgroups relative to the extent of interaction between subgroups (Frank et al., 2008). Although it has been assumed that the team is the appropriate unit of analysis in collective efficacy research, formal boundaries may be misleading and inappropriate when clusters or subgroups exist. Indeed, Brown et al. (1996) suggested that dispersion may emerge as a result of subgroups within the team, and recommended investigating how often subgroups occur in teams along communication and social interaction patterns. Although there is a lack of research on subgroups and collective efficacy, teams with communication and friendship subgroups are likely to have members with dispersed collective efficacy beliefs because information pertaining to the team's functioning and social comparison is constrained within cohesive clusters.

If there is evidence that subgroups based on communication and friendship ties exist within teams and that such subgroups influence collective efficacy dispersion, then it is important to understand the extent to which subgroups align according to collective efficacy beliefs. That is, dispersion at the team level may be a result of cohesive subgroups comprised of interacting members who develop shared collective efficacy beliefs over time. Previous studies have indicated that members of cohesive subgroups tend to have similar beliefs as a result of interaction patterns (Bavelas 1950; Leavitt 1951; Smith, 1973). Accordingly, members of subgroups are likely to develop similar collective efficacy beliefs as frequent discussions about the team's functioning and affective relationships provide members with access to the beliefs of others. This implies that individuals' collective efficacy beliefs may be influenced by members of their subgroup. Indeed, conforming to norms in the subgroup contributes to homogeneity within subgroups and heterogeneity between subgroups (Frank et al., 2008). In this study, collective efficacy is modeled as a function of subgroup's prior mean level of collective efficacy to determine the relative influence of subgroup processes.

In contrast to typical social interaction measures that ask individuals to rate the general level of interaction among team members, social network techniques provide a comprehensive description of group interaction. Traditional measures of social interaction assess individuals' perceptions regarding how frequently team members as a whole communicate or engage in personal relationships with each other. In contrast, a social network approach captures the complete network of relationships by asking each individual to indicate their interactions or relations with every member of the social system. An added advantage is that social network analysis examines structural properties of teams in relation to perceived outcomes, which avoids the problem of using percept-percept relations (Totterdell, Wall, Holman, Diamond, & Epitropaki, 2004). The application of social network methods to the study of collective efficacy has been proposed by researchers (Chow & Feltz, 2007; Gibson, 1999). For instance, Gibson (1999) suggested that "applying techniques from social network analysis would shed additional light on the patterns of connections between members and factors influencing how group members perceive, weight, and combine information in forming efficacy beliefs" (p. 150). In response, the present study uses group level social network measures (density, centralization, and subgroups) to predict collective efficacy dispersion.

To establish collective efficacy dispersion as a meaningful unit level variable, the construct must be related to important group outcomes. Previous studies have found that aggregated collective efficacy is a positive predictor of team performance (Gully et al., 2002). However, a fuller understanding of this relationship could be achieved through the simultaneous examination of within-team variability in group members' judgments. Researchers have proposed that collective efficacy dispersion moderates the relationship between aggregated collective efficacy and team performance such that, the relationship is stronger when members' beliefs display higher levels of perceptual consensus (Gully et al., 2002; Kozlowski, Gully, Nason, & Smith, 1999). Support for the moderating influence of collective efficacy dispersion on team effectiveness has been provided with dyads performing an experimental task (Arthur et al., 2007). A logical extension that supports the generalizability of Arthur and colleagues (2007) findings is to examine collective efficacy dispersion as a moderator of the aggregated collective efficacy-team performance relationship with teams comprised of multiple members performing meaningful tasks in their natural environment.

In addition to team performance, collective efficacy dispersion may moderate the relationship between aggregated collective efficacy and group affective states such as team commitment. Team commitment reflects individuals' desire and resolve to continue playing with their team (Scanlan, Carpenter, Schmidt, Simons, & Keeler, 1993). It is a motivational force that has implications for the amount of effort put forth and psychological withdrawal. The relationship between aggregated collective efficacy and team commitment should be stronger when dispersion is low rather than high because perceptual consensus fosters identification with the team and facilitates consistent affective responses (Gonzalez-Roma et al., 2002; Lindell & Brandt, 2000).

Contextual Factors

The context chosen for the current investigation was sport. Team sports provide an optimal context in which to study the development of collective efficacy through social interaction patterns because athletic teams represent intact units performing meaningful tasks in complex environments where members share a common purpose and experience similar events. Furthermore, unlike many teams found in organizational settings, sports teams receive frequent feedback where individuals attempt to make sense of previous performances by engaging in communication and social comparison processes with other teammates. Another advantage of using sports teams to better understand collective efficacy dispersion is that there are identifiable and relevant stages of team development. For instance, a competitive season is characterized by a beginning, middle, and end. Previous research suggests that team members' collective efficacy beliefs become more homogenous over time (Jung & Sosik, 2003). Thus, using team sport as a context to investigate why some teams develop more interrelated beliefs than others allows for an examination of this process among teams at similar points in time.

Women's intercollegiate softball was selected for this study for conceptual reasons and to further advance this line of inquiry with an underrepresented type of sport. Softball is a team sport in which only women participate at the intercollegiate level. Therefore, differences due to gender and sport are essentially controlled for by using women's softball teams. While this may limit the generalizability of the findings, the internal validity is strengthened. Previous research on collective efficacy has focused almost exclusively on highly interdependent sports such as football (Myers, Feltz, & Short, 2004), hockey (Feltz & Lirgg, 1998), and basketball (Watson et al., 2001). Unfortunately, little is known about the development of collective efficacy in sports that are characterized by lower levels of system interdependence. Team sports can be viewed along a task interdependence continuum with coactive sports (e.g., golf) at the low end and highly interdependent sports (e.g., soccer) at the high end. Located in the middle of the continuum are sports that require moderate levels of coordination and interaction among members such as baseball and softball. Finally, intercollegiate softball teams were selected over other competitive levels such as high school or club because rosters and team performance statistics are easily accessible from college and conference websites.

Purpose of the Study

The primary purpose of this study was to examine communication and friendship networks as antecedents of collective efficacy dispersion. This study extends previous research by examining collective efficacy dispersion as a focal variable and employs a social network framework to understand how collective efficacy beliefs develop as a function of interpersonal relations. A secondary purpose of this study was to establish the construct validity of collective efficacy dispersion by investigating the moderating influence on team performance and commitment.

Hypotheses

1. The density of a team's communication network is negatively related to collective efficacy dispersion, while controlling for prior levels of dispersion.
2. The density of a team's friendship network is negatively related to collective efficacy dispersion, while controlling for prior levels of dispersion.
3. Centralization of a team's communication network is positively related to collective efficacy dispersion, while controlling for prior levels of dispersion.
4. Centralization of a team's friendship network is negatively related to collective efficacy dispersion, while controlling for prior levels of dispersion.
5. Subgroup communication is positively related to collective efficacy dispersion, while controlling for prior levels of dispersion.

6. Subgroup friendship is positively related to collective efficacy dispersion, while controlling for prior levels of dispersion.
7. Collective efficacy dispersion moderates the relationship between aggregated collective efficacy and team performance such that, the relationship will be stronger when collective efficacy dispersion is low rather than high.
8. Collective efficacy dispersion moderates the relationship between aggregated collective efficacy and team commitment such that, the relationship will be stronger when collective efficacy dispersion is low rather than high.

Research Questions

1. Do subgroups based on communication ties exist within teams?
2. Do subgroups based on friendship ties exist within teams?
3. Do communication subgroups align by collective efficacy beliefs?
4. Do friendship subgroups align by collective efficacy beliefs?
5. Are individuals' collective efficacy beliefs influenced by members of their communication subgroup?
6. Are individuals' collective efficacy beliefs influenced by members of their friendship subgroup?

Delimitations

The findings are limited to intercollegiate women's softball teams, and thus may not generalize to other populations. For instance, the results may not be applicable to softball teams at different competitive levels, sports characterized by lower or higher task interdependence, or men's sports in general. Communication and friendship interactions on women's teams may be different from interactions on men's teams.

Further, some of the measures employed such as the collective efficacy questionnaire may only be appropriate for intercollegiate softball teams.

Definitions

1. *Centralization:* the extent to which a network revolves around a central actor; the sum of the differences between the largest centrality score and all other observed centrality scores, divided by the maximum possible sum of differences in actor centrality.
2. *Collective efficacy:* a team's belief in their capabilities to organize and execute the courses of action necessary to produce certain levels of attainments.
3. *Collective efficacy dispersion:* the degree of within-team variability in group members' collective efficacy beliefs.
4. *Communication network:* task-related exchanges among team members pertaining to the team's functioning such as discussing the team's strengths and weaknesses, performances, or goals.
5. *Density:* a measure of the interconnectedness of actors in a network; the proportion of ties in a network relative to the total number of possible ties in a network.
6. *Friendship network:* expressive interaction or affective relationships among team members; very good friends, seen socially outside of team-related activities.
7. *Klique Finder*: a program that is based on a general algorithm for identifying cliques (clusters or subgroups) of actors in a network.

8. *Run differential:* the number of runs scored minus the number of runs allowed divided by the number of games played.
9. *Social network analysis:* a set of techniques that map and measure relationships and flows between actors in a network.
10. *Subgroups:* non-overlapping cohesive clusters in terms of a concentration of interactions within subgroups relative to the extent of interaction between subgroups.
11. *Team commitment:* a team's desire and resolve to continue playing with their team.
12. *Team performance:* a team's winning percentage; the number of wins divided by the number of games played

CHAPTER 2

REVIEW OF LITERATURE

The purpose of this chapter is to provide a review of literature that is relevant to the variables and procedures in this study. This chapter begins by providing a rationale for conceptualizing collective efficacy dispersion as a theoretical construct based on conceptual contributions and empirical research. Next, research that has examined social interaction and shared beliefs is presented and integrated with collective efficacy. This is followed by a summary of social network analysis including research on communication and friendship networks, as well as group level metrics that describe the structure of various networks. Finally, research pertaining to collective efficacy dispersion as a moderating variable is discussed.

Dispersion as a Group-Level Construct

Elemental composition models are concerned with situations in which data collected at lower level units are combined to establish the higher level construct (Chan, 1998). For instance, collective efficacy is an emergent group-level construct that is derived or composed from members' individual perceptions. Bandura (1997) has suggested two methods for assessing collective efficacy that reflect different forms of composition. The first method aggregates team members' individual perceptions of self-efficacy (i.e., direct consensus), while the second method aggregates team members' individual perceptions of collective efficacy (i.e., referent-shift consensus). While both methods have been used in collective efficacy research, the majority of studies have preferred the individual perceptions of collective efficacy method because it is a better predictor of group performance (Feltz & Lirgg, 1998; Myers, Feltz et al., 2004).

In composition based on referent-shift consensus, the basic content of the efficacy perception is unchanged, but the referent of the content has changed from the self to the team (Chan, 1998). Researchers using referent-shift consensus will assess team members' individual perceptions of collective efficacy and then calculate the degree of within-team agreement as an index of consensus. If a sufficient level of within-team consensus is demonstrated, the individual perceptions are aggregated to form the higher level construct of shared collective efficacy. Thus, collective efficacy is operationalized as the mean of team members' collective efficacy beliefs and the degree of within-team variability is used as a statistical prerequisite to justify aggregation (e.g., Feltz & Lirgg, 1998; Prussia & Kinicki, 1996). A limitation of this approach is that it dichotomizes within-group variance and assumes that dispersion is the same across groups. However, teams that reach a sufficient of level for aggregation do not necessarily have the same degree of within-team variation.

A dispersion theory moves beyond the dichotomous view of aggregation and is defined as "an argument for the construct validity of dispersion along a specific variable" (Brown et al., 1996, p. 10). That is, dispersion is conceptualized as a focal construct instead of merely a statistical prerequisite for aggregation. Whereas referent-shift composition uses within-group consensus as a necessary precondition for the construct validity of the higher level construct, dispersion composition uses within-team variability as the operationalization of the group level construct (Chan, 1998). Thus, groups can be characterized along a continuum from high dispersion to low dispersion. An implicit assumption of dispersion theories is that the degree of within-team variability may be of theoretical interest and explain individual and team-related outcomes, or may moderate group-level effects.

Despite conceptual arguments (Brown et al., 1996; Chan, 1998; James, Demaree, & Wolf, 1984; Lindell & Brandt, 1997), dispersion constructs have received little empirical examination. An exception is perceived climate, which shares similar characteristics to collective efficacy in that both constructs require composition models where consensus is used to justify aggregating lower level responses (i.e., psychological climate) to represent the higher level construct (i.e., organizational climate). Climate strength, which refers to the degree of within-team variability in members' perceptions of climate (stronger climates have lower levels of within-group variability), has been found to account for unique variance in important organizational outcomes beyond the magnitude or aggregate of climate perceptions (Bliese & Halverson, 1998; Gonzalez-Roma et al., 2002; Schneider, Salvaggio, & Subirats, 2002). For instance, Bliese and Halverson (1998) examined the influence of climate strength on units' average psychological well-being with U.S. Army companies. They found that after controlling for aggregated climate perceptions, climate strength in leadership and peer relations predicted companies' average psychological well-being. Schneider and colleagues (2002) investigated whether climate strength moderated the relationship between bank employee ratings of service climate and customer perceptions of service quality. They found that the relationship between average climate perceptions and customer satisfaction services was stronger for units with high climate strength (i.e., lower within-team variability) for managerial practices.

Similar to climate strength, theorists have asserted that collective efficacy dispersion may provide insight into team functioning and performance beyond the mean of collective efficacy (Chan, 1998; DeRue et al., in press; Moritz & Watson, 1998). To date, only one empirical study has investigated collective efficacy dispersion as a focal variable. Arthur et al. (2007) explored the relationship between the degree of within-team variability in collective efficacy and team performance with 85 male dyadic teams performing an information processing task that was highly interdependent and complex. A videogame-based aviation task (i.e., Space Fortress) was employed where participants performed simultaneously each half of the task components (pilot-gunner functions and copilot mine-missile manger functions). Participants were administered a collective efficacy questionnaire at three time points over a 2-week period, which asked "How confident are you in the ability of your team to play Space Fortress?" and "If your team played Space Fortress in competition with 10 other teams, how do you think your team will place?" At each administration occasion, dyads performed two test games in which trainees alternated task roles. Team performance was calculated by taking the mean of the total scores from the two test games. The authors found partial support for the predictive validity of collective efficacy dispersion. Dyads with higher levels of within-team agreement outperformed dyads with lower levels of agreement, after controlling for collective efficacy magnitude. Findings from this study provide preliminary empirical support for the construct validity of collective efficacy dispersion, though it is difficult to draw substantive conclusions based on one study. Whether the findings generalize to intact teams comprised of several members performing in their natural environment is unknown. More importantly, if the degree of within-team variability is of substantive interest to researchers and practitioners, then it is important to understand the factors that contribute to perceptual consensus or dispersion in group members' collective efficacy beliefs.

Social Interaction and Shared Beliefs

Several theoretical frameworks suggest that social interaction underlies agreement or disagreement within a group. One of the first theories to recognize the importance of interpersonal interaction in the development of shared perceptions was social comparison theory (Festinger, 1954). Social comparison theory explains how individuals evaluate their own opinions and attitudes by comparing themselves to others. The theory posits that attitude formation results from a social comparison process where individuals weigh and integrate the attitudes of similar others. Other frameworks such as action theory (Silverman, 1971) suggest that interpersonal interactions with others cause people to modify and transform social meanings. An action theory perspective suggests that people who interact with each other in a group tend to attach similar meanings to organizational events, while people involved in different interaction groups attach different meanings to the same events (Rentsch, 1990). Symbolic interactionism posits that meanings of environmental events are formed in the context of social interaction and modified through interpretation processes (Blumer, 1969). Studies using symbolic interactionism suggest that individuals interacting with each other in work place develop similar perceptions of the environment over time (Schneider & Reichers, 1983). Symbolic interaction involves sense-making interaction where members engage in inductive and exploratory exchanges concerning the meaning of events in a quest for perceptual consensus (Zohar

& Tenne-Gazit, 2008). Finally, social identity theory (Tajfel & Turner, 1979) was developed to understand the psychological basis of intergroup discrimination and is concerned with explaining why individuals in groups adopt shared attitudes. The theory posits that group identification promotes shared social agreement among group members. Taken together, these different theoretical perspectives suggest that shared perceptions develop from prolonged interaction, whereas divergent beliefs arise from a lack of social interaction.

Previous research on climate strength (i.e., within-group variability in climate perceptions) has provided evidence for the influence of social interaction on shared perceptions. Social interaction among unit members fosters similarity in psychological climates and promotes the emergence of shared climate perceptions (Klein et al., 2001; Gonzalez-Roma et al., 2002). Klein and colleagues (2001) investigated social and work-related interaction as an antecedent of within-group variability in group members' perceptions of their work environment. The social interaction scale asked group members to describe how frequently they interacted with each other as friends, whereas the work interdependence instrument required group members to rate the extent to which they coordinated with and depended on each other to accomplish their work tasks. Group level analyses revealed that units with greater social and work-related interaction had less within-group variability in responses to financial resource availability and plant innovativeness than units with lesser amounts of interaction. Gonzalez-Roma and colleagues (2002) examined social interaction as an antecedent of climate strength with 197 work units of the regional public health service. Social interaction was measured by asking unit members to report how often they talked about the work unit's goals, work planning, and functioning with their unit work mates. The authors found that social interaction significantly correlated with climate strength in goals orientation and innovation. Units with higher levels of social interaction among group members regarding work-related issues (i.e., goals, planning, and functioning) had higher levels of perceptual consensus in climate perceptions. Results on climate strength suggest that group level social interaction is an antecedent of within-team variability in group members' climate perception. Teams in which members perceive high levels of within-team interaction develop similar perceptions, whereas teams in which group members perceive a lack of social interaction develop dispersed perceptions. An alternative explanation is that individuals choose to interact with other group members who have similar perceptions. Previous studies that have examined the relationship between group interaction and the development of shared perceptions have failed to obtain an initial measure of the perception of interest which makes it difficult to ascertain the direction of causality.

Several theorists have suggested that shared collective efficacy beliefs emerge from interpersonal interaction. Gibson (1999) proposed that collective efficacy develops "as group members collectively acquire, store, manipulate, and exchange information about each other and about their task, context, process, and prior performance" (p. 138). Conversely, differences in group members' perceptions of the team's capability to succeed would arise when individuals fail to obtain and exchange information with each other. Jung and Sosik (2003) have also noted the role of social interaction in the emergence of shared collective efficacy beliefs. In discussing their finding that student groups working on decision-making projects developed more homogenous perceptions of collective efficacy over the course of a semester, they speculated that substantial social interaction and perspective taking was a necessary precondition for the emergence of shared beliefs. Based on these assertions, the extent to which group members discuss and share their perspectives about the team's functioning may determine differences in collective efficacy dispersion among teams. Teams in which group members engage in frequent communication should develop more interrelated beliefs, whereas teams that lack social interaction should develop more dispersed beliefs. However, because the degree of social interaction has not been directly assessed in relation to collective efficacy, these propositions are only speculative.

The notion that collective efficacy beliefs can be influenced through social interaction has been implied by researchers who have critiqued the group discussion method of collective efficacy assessment. In contrast to the standard assessment procedure discussed earlier in this chapter, where members' individual perceptions of collective efficacy are aggregated (i.e., rate your confidence in the team's ability), the group consensus approach uses group discussion to obtain a single estimate (e.g., Gibson et al., 2000; Jung & Sosik, 2003). Researchers that use the group discussion method first proceed by having team members rate their confidence in the team individually (as in the individual collective efficacy method), and then as a collective group. During group assessment, team members are allowed to interact with each other to discuss their personal beliefs regarding the team's ability to be successful until a forced consensus is reached. Bandura (1997) has criticized the group-based approach because social persuasion and pressure to conform may produce inaccurate estimates of collective efficacy. For instance, an individual may agree with the team estimate that is derived based on interactions with vocal members when in reality their perception remains unchanged. While the group consensus approach may reveal that individuals have deviated from their held belief erroneously, it is also plausible that individuals modify or change their perception of collective efficacy as a result of information exchanges with other group members. Convincing arguments or access to new information are weighed against the individual's initial belief. Studies that have employed both methods have not measured individual perceptions of collective efficacy a second time following group discussion and thus, it is unknown whether group members actually changed their belief or simply conformed to reduce conflict.

Social Networks

Although social network analysis has been used since the mid-1930s, interest in social networks has begun to grow at an increasing rate. Fields such as sociology, psychology, epidemiology, and physics are now adopting a network perspective to study complex issues. In organizational psychology alone, social network techniques have been used to examine a wide range of organizational phenomena such as social capital, embeddedness, network organizations, board interlocks, joint ventures and inter-firm alliances, knowledge management, social cognition, and group processes (see Borgatti & Foster, 2003). Surprisingly, the application of social network analysis in sport psychology research has failed to match the progress of other disciplines. This is unfortunate considering that social network techniques are particularly useful for stating social properties and processes and rigorously defining theoretical constructs (Freeman, 1984).

A social network consists of a set of actors and the ties between these actors (Wasserman & Faust, 1994). The actors may represent different levels of analysis including individuals, teams, organizations, societies, or concepts. A wide range of ties have been examined that reflect different types of relations or interactions among actors such as communication (e.g., who talks to whom), affective (e.g., who is friends with whom), proximal (e.g., who is physically close to whom), and cognitive (e.g., who knows whom). The critical difference between social network techniques and traditional analytic methods is that it uses structural or relational information of a group rather than attribute data. Based on the pattern of relationships between individuals in a network, measures of social structure can be calculated that may explain the transfer of information, beliefs, and behaviors.

While actors are often involved in multiple types of relations with other members in a network, certain types of ties are more relevant to social influence than others. Two types of ties that have been studied in relation to important individual and organizational outcomes are communication and friendship networks. Communication networks reflect instrumental interactions that involve exchanges between members that are task-related. Examples of communication ties include receiving advice about work-related problems, discussing work-related topics, and interacting with people in order to complete a task. Task-related information exchanges provide pathways to coordinate existing activities and reinforce organizational norms. They have been found to predict influence acquisition (Brass, 1984), organizational power (Burkhardt & Brass, 1990), risk taking, acceptance and information access (Ibarra & Andrews, 1993), work-related knowledge (Morrison, 2002), performance (Sparrowe et al., 2001), perceptions of learning and enjoyment (Baldwin, Bedell, & Johnson, 1997) and self-efficacy (Burkhardt, 1994).

Friendship networks represent affective or expressive ties among members. In contrast to communication networks which are sources of information and advice, friendship networks are based on intimacy and trust, and are important sources of social support (Ibarra, 1993; Lincoln & Miller, 1979). In addition, friendship ties tend to be more stable and enduring than communication relations (Shah, 2000). Close friends or individuals who one consults or gets help from about personal issues define the friendship network. Because of the level of affective closeness reflected in a friendship network, group members tend to share acceptable or attitude-reinforcing information to reduce stress and conflict (Krackhardt, 1999). Similar to communication ties, friendship networks predict important outcomes such as organizational commitment (Morrison, 2002), team-based learning satisfaction (Baldwin et al., 1997), resource sharing during crisis (Krackhardt & Stern, 1988), and career-related decision making (Kilduff, 1990).

There tends to be some overlap between communication ties and friendship ties in a network (Borgatti & Foster, 2003). That is, people often communicate with individuals who are also considered their close friends. However, the two types of ties are not only conceptually distinct (a person may communicate with someone who is not their friend), but the theoretical mechanisms of social influence are also different. Communication ties are pathways for the transfer of knowledge and information. Discussion and perspective sharing about task-related issues such as previous performance resolve uncertainty and provide actors with access to new information and a better understanding of team events. Friendship ties are pathways that produce social influence via interpersonal comparison and social modeling where similar or affectively close significant others provide a frame of reference for managing uncertainty (Burt, 1987).

Social Network Measures

While communication and friendship ties describe particular types of relations between actors in a network, group level social network metrics describe the structure of these ties. An advantage of this approach is that the metrics can be used to characterize teams according to their pattern of communication and friendship interactions. Consequently, the structure of teams' communication and friendship networks can be examined in relation to differences in group level outcomes such as collective efficacy dispersion. The most common group level network measure is structural density (Scott, 2000). Density is a measure of the interconnectedness of actors in a network and is defined as the proportion of ties in a network relative to the total number of possible ties. For instance, if Team A and Team B both had 5 group members, there would be 20 possible ties within each team (assuming directional relations). If Team A had 10 pairs of ties and Team B had 6 pairs of ties, then Team A would have a denser network. The density coefficient is at a minimum when no direct ties exist between actors in a network and at a maximum when every actor has a tie with all other members.

Previous organizational studies that have employed social network methods have demonstrated that teams with higher levels of communication and friendship density outperform teams with lower levels of density (Baldwin et al., 1997; Reagans & Zuckerman, 2001). Reagans and Zuckerman (2001) examined the relationship between communication density (i.e., the average frequency of communication among team members) and team performance with 224 corporate research and development teams. The social network data were obtained through a sociometric instrument in which members were asked to indicate how frequently they communicated with other members of the same team. They found that teams averaging more frequent communication among members achieved higher levels of productivity because dense patterns of local interaction provided a basis for coordination and collective action. Baldwin and colleagues (1997) examined the influence of communication and friendship network ties on team performance with MBA student teams. Communication relations were assessed by asking students to indicate the classmates who were important sources of school-related advice or whom they approached for school-related problems, while friendship ties were measured by asking respondents to indicate the individuals who were very good friends, people whom they saw socially outside of school. Results demonstrated that groups that reported higher levels of communication density had stronger perceptions of shared work load and team interaction effectiveness which in turn, predicted team grade. In addition, teams that reported denser friendship ties had stronger perceptions of team interaction effectiveness which in turn, also contributed to student teams' grades. A meta-analysis of 37 studies involving 3,098 intact teams revealed that teams with densely configured instrumental and expressive ties performed higher and were more committed to staying together than teams with sparsely configured ties (Balkundi & Harrison, 2006).

Not only does network density improve team performance, but it may also facilitate the development of shared beliefs (Baerveldt & Snijders, 1994; Friedkin, 1984; Zohar & Tenne-Gazit, 2008). Indeed, Brass, Butterfield, and Skaggs (1998) have argued that dense networks may be a necessary requirement for the development of shared norms and values. Network density fosters identification with the group, enhances coordination and collective action, and promotes mutual trust (Coleman, 1988; Portes & Sensenbrenner, 1993). In dense networks, group members frequently share information and compare themselves to others, which thereby facilitates the diffusion of beliefs and social modeling processes. Conversely, in sparse networks, information sharing and interpersonal comparisons are constrained which produces isolated opinions and provides fewer opportunities for social comparison. Indeed, a team of isolates will have difficulty exchanging task-related issues because there are no established patterns of ties to convey the information (Balkundi & Harrison, 2006).

Evidence supporting a potential relationship between density and collective efficacy dispersion comes from the group cohesion literature. Although conceptually distinct, researchers have used density as a group-level measure of cohesion (Festinger, Schachter, & Black, 1950; Frank 1996, Frank & Yasumoto 1998). Although several definitions of group cohesion have been proposed (Mudrack, 1989), sport and organizational research typically conceptualize group cohesion as a cognitive, motivational, or affective group-level attribute. For instance, Carron, Brawley, and Widmeyer (1998) have defined group cohesion as "a dynamic process that is reflected in the tendency for a group to stick together and remain united in the pursuit of its instrumental objectives and/or for the satisfaction of member affective needs" (p. 213). Measures of group cohesion based on such definitions use attitudinal scales where team members rate their level of attractiveness to the group (e.g., Carron, Widmeyer, &

Brawley, 1985). In contrast, network density provides a measure of cohesion based on direct interactions and relationships within teams.

Theorists have asserted that group cohesion is an antecedent of collective efficacy (Zaccaro at al., 1995). Group cohesion is a multidimensional construct that involves both task and social factors. Task cohesion reflects members' feelings about the similarity, closeness, and bonding within the team as a whole around the group's goals and objectives. Previous studies have found that individuals with higher levels of task cohesion have stronger perceptions of collective efficacy than individuals with lower levels of task cohesion (Kozub & McDonnell, 2000; Paskevich et al., 1999; Spink, 1990). For example, Paskevich and colleagues (1999) investigated the influence of group cohesion on collective efficacy with university and club volleyball teams. They found that the task cohesion subscales (individual attraction to the group-task and group integration-task) distinguished athletes that were either high or low in collective efficacy. Players with higher levels of task cohesion held stronger beliefs about the team's ability to be successful than individuals with lower levels of task cohesion. Kozub and McDonnell (2000) reported similar findings with rugby players in that task cohesion accounted for 32% of the variance in members' collective efficacy beliefs.

Social cohesion reflects group members' feelings about the similarity, closeness, and bonding within the team as a whole around the group as a social unit. Although a weaker source of collective efficacy than task cohesion, studies have shown that social cohesion influences beliefs regarding team effectiveness (Kozub & McDonnell, 2000; Spink, 1990). In one of the first studies to examine collective efficacy, Spink (1990) proposed a relationship between group cohesion and collective efficacy based on previous research suggesting that cohesion and efficacy were important determinants of sport performance. Participants were volleyball players from recreational and elite teams participating in an annual tournament. Separate analyses were conducted, which revealed that group cohesion was a positive predictor of collective efficacy for players of elite teams, but not for players of recreational teams. That is, athletes of elite volleyball teams who reported that their team was socially cohesive held stronger beliefs about their team's capabilities. Further evidence for the influence of social cohesion on collective efficacy was demonstrated by Kozub and McDonnell (2000) who found that rugby players with higher perceptions of social cohesion had a stronger sense of collective efficacy than players with lower perceptions of social cohesion.

Clearly, research suggests that higher levels of task and social cohesion are associated with stronger perceptions of collective efficacy. Further, although conceptually different, communication and friendship density may serve as proxies for task and social cohesion, respectively. For instance, task cohesion implies that members are involved in frequent task-oriented exchanges, while social cohesion suggests that members view their team as an important social group. Indeed, Zaccaro at al. (1995) has speculated that groups may not be as cohesive if some members perceive that the team is strong, while others believe that it is weak.

Whereas density reflects the general level of cohesion in a network, centralization describes the extent to which the cohesion is organized around central positions (Scott, 2000). Centralization is a group-level social network metric that is a measure of variability, dispersion, or spread of social ties (Wasserman & Faust, 1994). It represents the extent to which a network revolves around a highly central actor

(Freeman, 1979). Completely centralized networks resemble a perfect star where one central actor is tied to all other members who are not tied to each other. Conversely, decentralized networks exist when all network members have the same centrality score.

Centrality is an individual level variable that reflects the extent to which an actor is directly tied to other members in a network. All actors in a social network have a centrality score. Actors who occupy more central positions in a network have greater levels of power (Brass, 1984), job satisfaction (Dean & Brass, 1985), influence in decision-making (Friedkin, 1993), and performance (Baldwin et al., 1997; Sparrowe et al., 2001). While centrality reflects an individual's position in a network, centralization describes the network structure as a whole. However, the positive consequences associated with centrality at the individual level may not necessarily extend to centralization at the group level. Early research on centralization employed experimental designs where the pattern of communication among group members was manipulated by controlling who could send information to whom (Bavelas, 1950; Leavitt, 1951; Shaw, 1954, 1964). Results from these studies found that centralized communication structures were beneficial for simple tasks, while decentralized communication networks were superior for complex tasks. Recent studies on centralization have replicated earlier findings with intact groups in the field. For instance, Sparrowe and colleagues (2001) investigated the influence of advice centralization and density on performance with 38 work groups. While density was unrelated to team performance, groups with decentralized advice patterns performed better than groups with centralized advice patterns. Cummings and Cross (2003) investigated structural properties of a network with 182 work groups in a global organization. They found that groups constrained by centralized communication structures performed worse than groups with more integrative structures.

Similar to structural density, centralization may affect the emergence of shared or dispersed perceptions at the team level, though the direction of effect may differ depending on the type of tie. Zohar and Tenne-Gazit (2008) examined communication and friendship centralization as an antecedent of climate strength for safety with male infantry soldiers on 45 platoons undergoing advanced training camp for army field units. A sociometric instrument was administered in which participants were asked how much they talked with each of the platoon members on subjects that were activity or mission related (i.e., communication network) and with which of their platoon members they consulted or received help from about personal issues (i.e., friendship network). The authors hypothesized that units with decentralized communication structures would have less within-team variability in climate perceptions because a wider spread of member exchanges offers better opportunities for social diffusion of information. Conversely, they hypothesized that platoons with more centralized friendship networks would have less climate dispersion because a central actor would provide a common referent for peripheral members to compare and model themselves after. They reasoned that individuals who were involved in a dyadic comparison process with few members were more likely to hold similar beliefs because they agreed with the same significant other. Consistent with their hypotheses, unit members' safety climate perceptions demonstrated higher levels of agreement when communication ties were less centralized and when friendship ties were more centralized.

The opposing effects of communication and friendship centralization can be explained by the different mechanisms of social influence (Zohar & Tenne-Gazit, 2008). In a communication network, information serves as the conduit in which the beliefs of group members transfer to others. Decentralized communication structures facilitate information flow throughout the network (Cummings & Cross, 2003), and increase the likelihood that members will receive access to the views of all others. In contrast, centralized networks constrain the flow of information which is concentrated around a dominant actor. When information is transmitted to relatively few members, the central actors obtain access to the perspectives of the peripheral members, while the network as a whole receives limited information. Whereas information defines the communication network, the pathway of social influence in a friendship network centers on interpersonal comparison or social modeling. Centralized friendship networks revolve around a central actor who is friends with the majority of team members who are not friends with each other. Because friendship ties are based on closeness and the central actor has the highest affective visibility, peripheral members tend to conform to the central belief (Zohar & Tenne-Gazit, 2008).

While the findings of Zohar and Tenne-Gazit (2008) demonstrate support for the predictive validity of group level structural properties on the development of perceptual consensus and provide a general framework for the examination of social interaction as a source of collective efficacy dispersion, there are some limitations that should be noted. The primary limitation was that a previous measure of within-team variability in unit members' perceptions of safety climate was not obtained, which makes it difficult to determine the direction of influence. For instance, did social interaction produce shared beliefs or did individuals choose to interact with group members who held similar perceptions? This limitation has been observed in the social interaction-shared perception literature (e.g., Gonzalez-Roma et al., 2002) as well as social network research (e.g., Rentsch, 1990). The lack of longitudinal research makes it difficult to determine the influence of the network on the hypothesized effects (Lazer, 2001). While multiple assessments of the social network may provide the clearest understanding regarding the issue of influence or selection, the difficulty of collecting social network data poses a problem. An alternative involves measuring the hypothesized outcome (e.g., initial collective efficacy dispersion) prior to the social network to control for previous differences between teams. Another limitation of the Zohar and Tenne-Gazit (2008) study was that networks were defined as the unit members only and thus, did not include group leaders. However, social interactions between individual group members and the team leader are just as important as interactions among group members, and may influence group-level social network metrics.

Subgroups

Previous studies that have examined subgroups have focused on differences between group members on demographic attributes such as age, sex, ethnicity, tenure, and functional area (Jackson, May, & Whitney, 1995). This line of research has produced equivocal findings regarding the consequences of subgroups. One perspective suggests that subgroups have a negative influence on team functioning because differences among members hinder communication and social integration. Supporting this perspective, research has found that teams with subgroups perform at lower levels than both highly homogeneous and highly heterogeneous teams as a result of communication problems, increased conflict, and lower levels of team identity (Earley & Mosakowski, 2000). The presence of subgroups may create social factions within teams where individuals only interact with other members of their subgroup with little interaction between members of different subgroups. An alternative perspective is that subgroups have a positive influence on team functioning. Research supporting this perspective suggests that subgroups contribute to higher levels of creativity, richer information processing, and higher quality decision-making (McGrath, 1984; Jackson, 1992; Lovelace, Shapiro, & Weingart, 2001). Teams with subgroups engage in more learning behavior than teams that lack subgroups because differences across subgroups ensure that a diversity of insights is considered (Gibson & Vermeulen, 2003).

A social network approach to identifying cohesive subgroups focuses on social interactions rather than demographic characteristics (Frank, 1995). This perspective defines subgroups as clusters of actors who engage in more frequent relations with members internal to their subgroup than with members external to their subgroup. Similar to density and centralization, subgroups are examined according to communication and friendship ties in this study. Subgroups may produce lower levels of emotional attachment to the group as a whole if members identify with their subgroup more strongly than their team (Paxton & Moody, 2003). In addition, consensus formation may depend on whether subgroups exist within teams (Brown et al., 1996). For instance, teams with subgroups based on communication and friendship interactions may have higher levels of collective efficacy dispersion than teams without subgroups. Although there may be clusters of local agreement within subgroups, the differences between subgroups are likely to create dispersion at the team level. In subgroups, there tends to be informational redundancy among members, which reinforces certain attitudes and beliefs, eventually becoming part of the subgroup's normative structure. While the dense pattern of interactions within cohesive subgroups facilitate information flow and social comparison processes among actors of the same subgroup, members of different subgroups have limited access to the beliefs and perspectives of others. The lack of information sharing and knowledge transmission produces homogenous beliefs within clusters and heterogeneous beliefs between clusters.

Although a social network approach to identifying subgroups focuses on dense patterns of social interaction, research suggests that subgroups align by individuals' background characteristics, sentiments, and behaviors (Frank, 1995). That is, members of cohesive subgroups tend to have similar demographic characteristics, hold similar beliefs, and exhibit similar patterns of behavior. One belief that may be related to subgroup membership is collective efficacy. Indeed, researchers have speculated that subgroups based on collective efficacy may form within teams as a result of social interaction patterns among members (DeRue et al., in press). The formation of subgroups based on collective efficacy likely emerges through frequent discussions about the team's functioning and affective relationships which provide members with access to the beliefs of others.

An underlying premise of subgroups is that members of particular clusters develop similar attitudes and beliefs as a result of dense social interactions within their subgroup. Individuals may modify or change their personal beliefs through social influence processes exerted by proximal members. This implies that actors may be influenced by members of their subgroup. Previous research suggests that individuals, particularly females, are highly responsive to social norms in their local clusters (Frank et al., 2008). Just as the pattern of group interaction at the network level may explain between-team differences in collective efficacy dispersion, team members' perceptions of collective efficacy may depend on subgroup processes. Through communication exchanges and social modeling, individuals may modify or change their beliefs to match the perceptions of their subgroup members. This suggests that individuals' collective efficacy beliefs will be determined by their subgroup's prior mean levels of collective efficacy.

Collective Efficacy Dispersion as a Moderator

The relationship between collective efficacy and team performance has been well documented in the literature. Results from both laboratory (Hodges & Carron, 1992; Lichacz, & Partington, 1996) and field studies (Feltz & Lirgg, 1998; Myers, Feltz et al., 2004; Myers, Payment, & Feltz, 2004) have demonstrated that teams with stronger judgments regarding their coordinative capabilities outperform and persist longer than teams with weaker judgments. Feltz and Lirgg (1998) investigated relationships among aggregated self-efficacy, aggregated collective efficacy, and team performance with six male intercollegiate ice hockey teams over the course of a 32 game season. They found that aggregated collective efficacy predicted team performance within teams and across games, but aggregated self-efficacy did not. Myers, Feltz et al. (2004) replicated these findings with 10 intercollegiate American football teams and further extended this line of inquiry by demonstrating that aggregated collective efficacy was a positive predictor of subsequent offensive performance within weeks and across teams. Myers, Payment et al. (2004) examined the influence of collective efficacy on team performance over the course of a competitive ice hockey season within weekends with 12 female intercollegiate teams. The authors improved upon earlier research by statistically controlling for previous team performance. After controlling for Friday team performance, the influence of Saturday collective efficacy on Saturday team performance was positive and moderate. Taken together, these findings indicate that the magnitude of collective efficacy is positively related to team performance.

A primary limitation of previous collective efficacy-team performance studies is that the magnitude of collective efficacy has been emphasized, while the degree of within-team variability around the central belief has been neglected in the primary analyses. It has been proposed that collective efficacy dispersion may moderate the relationship between collective efficacy magnitude and team performance such that, the relationship will be stronger when members' beliefs are more interrelated than when they are dispersed (Gully et al., 2002; Kozlowski et al., 1999). Research has demonstrated that the relationship between aggregated group perceptions and team performance is moderated by the degree of within-team dispersion. As discussed previously, Schneider et al. (2002) examined whether climate strength moderated the relationship between bank employee ratings of service climate and customer perceptions of service quality. They found that interaction between climate strength for managerial practices and average climate perceptions explained unique variance in customer satisfaction services after controlling for main effects. As discussed earlier in this chapter, there is also some empirical evidence that suggests collective efficacy dispersion moderates the collective efficacy-team performance relationship (Arthur et al., 2007). The implication of this study is that the relationship between collective efficacy and team performance cannot be fully understood without consideration of collective efficacy dispersion.

While the majority of research has examined behavioral outcomes of collective efficacy such as team effectiveness, beliefs regarding the group's capabilities are also posited to influence team cognitive and affective states. For instance, collective efficacy influences team attributions (Chow & Feltz, 2008), shared mental models (Peterson, Mitchell, Thompson, & Burr, 2000), and precompetitive cognitive anxiety (Greenlees et al., 1999). In addition, teams with a stronger sense of efficacy set more difficult group goals and are more committed to those goals (Mulvey & Klein, 1998).

Just as teams with high collective efficacy tend to have members who are more committed to collective goals, such teams should also have members who are more attached to playing with their team. Conversely, on teams with low collective efficacy, group members may be less committed to their team and as a result, invest less time and effort into group endeavors. Previous research has found that teams with higher collective efficacy have greater team viability, which reflects group members' willingness to remain with the group (Pescosolido, 2003). A construct that is similar to team viability is commitment. Sport commitment has been defined as "a psychological construct representing the desire and resolve to continue sport participation" (Scanlan et al., 1993, p. 6). It is a motivational force for continued involvement, and reflects an important psychological underpinning of persistence. While the magnitude of collective efficacy may exert a direct influence on team commitment, the relationship may depend on the degree of within-team variability in group members' beliefs. Shared beliefs strengthen team identity and the value of team membership, which reduces psychological withdrawal (Roberson & Colquitt, 2005). Previous studies have found that perceptual consensus interacts with aggregated perceptions to affect the predictability of team affective states. For instance, Gonzalez-Roma et al. (2002) investigated whether climate strength moderated the relationship between work units' aggregated climate perceptions and their collective affective responses. They found that climate strength in innovation moderated the influence of work units' climate on average satisfaction and commitment, and that climate strength in goals orientation moderated the influence of work units' climate on average commitment. The authors reasoned that strong consensus fosters uniform affective responses, whereas weak consensus yields a larger variability in the associated affective responses.

Summary

Previous research has focused exclusively on the magnitude of collective efficacy, while treating the degree of within-team variability as measurement error. However, collective efficacy dispersion may provide insight into team functioning and performance beyond the magnitude of collective efficacy. A dispersion theory examines collective efficacy dispersion as a dependent variable with hypothesized antecedents and as a moderating variable with proposed team-related outcomes. Social network analysis provides techniques to measure the patterns of social interaction within teams which can be used to compare differences in collective efficacy dispersion between teams. Not only is there a lack of understanding regarding the emergence of within-team variability in group members' collective efficacy beliefs, but also the consequences of collective efficacy dispersion. The usefulness of a dispersion theory of collective efficacy can be recognized by demonstrating that it predicts important team outcomes such as performance and commitment.

CHAPTER 3

METHOD

Participants

Teams from the Midwestern and Eastern regions of the United States were contacted for recruitment in the study. Initially, 50 teams agreed to participate in this study and completed Time 1 measures. Of these teams, 46 completed both the Time 1 and Time 2 questionnaires. A MANOVA was run to determine whether the four teams that did not return the Time 2 questionnaires differed from the teams that completed both sets of questionnaires on various demographic, psychological, and performance variables (e.g., experience, years on the team, team size, collective efficacy, team commitment, and winning percentage). Results revealed that there were no significant differences on any of these variables. Thus, only the 46 teams that completed both Time 1 and Time 2 measures were used in the study and subsequent analyses.

The participants in this study were athletes (N = 763) and their head coaches (N = 46) from intercollegiate women's softball teams. Starters and nonstarters as well as position players and pitchers were included in this study. Athletes ranged in age from 18 to 24 years (M = 19.79, SD = 1.30), were members of their respective teams for 1 to 5 years (M = 2.09, SD = 1.08), and had played softball for 1 to 20 years (M = 12.20, SD = 3.49). Coaches (Female = 38, Male = 8) ranged in age from 24 to 68 years (M = 39.58, SD = 11.94), had coached softball for 2 to 35 years (M = 14.09, SD = 9.26), and were with their respective teams for 1 to 27 years (M = 8.37, SD = 7.56. The majority of teams in the study were from Division II and III (Division I = 1, Division II = 12, Division III = 30, NAIA = 3). Team size ranged from 10 to 24 players (M = 16.59, SD =

3.16), team mean playing experience ranged from 8.27 to 15.13 ($M = 12.16$, $SD = 1.33$), and team mean number of years on the team ranged from 1.57 to 2.58 ($M = 2.09$, $SD = .24$).

Procedure

Permission to conduct this study was obtained from the Institutional Review Board for Human Subject Research. Following approval, coaches were contacted via email requesting permission for their team to participate in this study. An explanation of the purpose and procedure of the research was provided to coaches of teams who agreed to participate in this study. Coaches were asked to provide information regarding the date of their first competition (to ensure that the Time 1 surveys were delivered) and the number of athletes on their team. In addition, because the sociometric instrument requires team members' names, coaches were asked to submit a team roster. Informed consent was obtained from all players and head coaches prior to data collection.

Data collection involved two time points. Time 1 data were collected at the beginning of the season, prior to the first scheduled competition. This time frame was selected to allow team members to develop an initial sense of collective efficacy that was not influenced by competitive feedback or team performance from the current season. It provided a baseline measure that was constant across all teams. At Time 1, athletes were administered demographics, collective efficacy, and team commitment questionnaires, while coaches completed demographics and collective efficacy. Time 2 data were collected at the middle of the season, after teams had played half of their scheduled competitions. Questionnaires that were administered to athletes at Time 2 included demographics, collective efficacy, team commitment, and the social network instrument. At Time 2, coaches were administered demographics, collective efficacy, and social network questionnaires. Team performance data in terms of winning percentage were obtained at two time points: current winning percentage (collected at Time 2: middle of season) and overall winning percentage (collected after all scheduled competitions had been completed). In addition, team statistics pertaining to runs scored and runs allowed were collected at the same time points (middle of the season and end of the season).

Questionnaires were administered before or after a selected practice, or at a team meeting, which was neither immediately before nor after a competition in order to avoid competition-specific responses. An athletic trainer was responsible for administering the questionnaires to athletes and the head coach. Participants were guaranteed confidentiality of their responses and were instructed to complete the questionnaires individually without conversing with teammates. Following completion, questionnaires were collected by the athletic trainer, placed in a sealed envelope to further ensure confidentiality, and mailed to the principal investigator using a prepaid postage return envelope.

Measures

Demographics. A demographic questionnaire was used to obtain background information from players and coaches. The athlete demographic questionnaire at Time 1 is presented in Appendix A. Items included age, NCAA Division, year in school (e.g., first-year, sophomore, junior, senior, fifth-year), total number of years playing softball, position(s) played, number of years on the team, and starter status. In addition, athletes were asked to indicate whether they were a team captain and whether they considered themselves to be a leader. The Time 2 athlete demographic questionnaire (see Appendix B) was similar to Time 1 with the exception of three additional items that assessed players' confidence in their coach's ability to: (a) communicate effectively with players, (b) build the mental skills of players, and (c) make critical coaching decisions. These three items were selected because of their congruence with the collective efficacy measure used in this study. Responses were made on a 5-point scale ranging from 1 *(cannot do at all)* to 5 *(highly certain can do)*. A confidence in coach score for each individual was calculated by averaging each athlete's responses to the 3-items, while a confidence in coach score for each team was calculated by aggregating team members' scores to the group-level. The internal consistency reliability for the confidence in coach scale was .92.

The coach demographic questionnaire is presented in Appendix C. Items included gender, age, number of years coaching the team, total number of years coaching softball, number of years playing experience, highest level of playing experience, and team's win/loss record. In addition, coaches were asked to rate the physical ability and teamwork ability of the athletes on their team this year, and the overall ability of the teams on their schedule on a scale from 1 *(very poor)* to 5 *(excellent)*.

Collective efficacy. The collective efficacy measure comprised 10-items and was developed in accordance with Bandura's (2006) recommendations. A conceptual analysis was conducted in consultation with players and coaches to identify important team performance competencies relevant to success in softball. The collective efficacy questionnaire is presented in Appendix D. Players and coaches were asked to rate how certain they were that their team as a whole could: (a) communicate well as a unit, (b) regain mental focus after an error/mistake, (c) avoid walking opposing batters, (d) consistently throw strikes, (e) outscore opponents, (f) consistently put the ball in play, (g) have a high fielding percentage, (h) hit with runners in scoring position, (i) successfully lay down bunts, and (j) make good decisions on the base paths. Although 11-point rating scales (i.e., 0% to 100% with intervals of 10%, or 0 to 10 with intervals of 1) have been recommended (Bandura, 2006), studies have found that efficacy scales employ too many categories (Zhu & Kang, 1998; Zhu, Updyke, & Lewandowski, 1997). An optimal rating scale offers a more accurate true score estimate of within-team variability (Linacre, 2002). Scales with more options can produce higher levels of variance simply because of properties of the scale (Brown et al., 1996). Collective efficacy instruments are particularly susceptible to this problem because most respondents only use the upper end of the rating scale (Myers & Feltz, 2007). Thus, collective efficacy ratings were made on a 5-point scale ranging from 1 *(cannot do at all)* to 5 *(highly certain can do)*. A collective efficacy score for each athlete and coach was calculated by averaging each person's responses to the 10-items, while a collective efficacy score for each team was calculated by aggregating team members' scores to the group-level. Internal consistency reliabilities for the collective scale were .89 at Time 1 and .89 at Time 2 for athletes. For the collective efficacy scale rated by coaches, the internal consistency reliabilities were .85 at Time 1 and .88 at Time 2.

Research that has conceptualized dispersion or within-team agreement as a focal variable has indexed the construct using r_{wg} (Arthur et al., 2007) and standard deviation (Klein et al., 2001; Schneider et al., 2002; Zohar & Tenne-Gazit, 2008). While cogent arguments have been provided in support of both conceptualizations, collective efficacy dispersion was operationalized as the standard deviation of members' collective efficacy beliefs because r_{wg} can exceed 1.00 on occasion and because most people think of dispersion in terms of standard deviation (Lindell & Brandt, 2000). Following procedures advanced by Klein and colleagues (2001), collective efficacy dispersion was calculated by averaging the standard deviation of group members' responses to each collective efficacy item. Averaging the standard deviations across the collective efficacy items rather than simply calculating the standard deviation of members' mean collective efficacy scores provides a more precise and comprehensive measure of dispersion. The dispersion index was normalized to account for team size differences by using the following equation: Log ($SD + 1/2n$), with higher scores reflecting higher levels of dispersion and lower scores reflecting higher levels of consensus.

Commitment. The team commitment questionnaire is presented in Appendix E. Team commitment was assessed using a modified 4-item measure of sport commitment (Scanlan et al., 1993). Sport commitment can be assessed at various levels of analysis such as commitment to a particular team, to a particular sport, or to sport in general. For purposes of this study, sport commitment was conceptualized as commitment to the team. Items included (a) "I am dedicated to playing with this team" (b) "It would be hard for me to quit playing with this team" (c) "I am determined to keep playing with this team" and (d) "I am willing to do almost anything to keep playing with this team." Ratings were made on a 5-point scale ranging from 1 *(not true at all for me)* to 5 *(completely true for me)* with higher scores representing greater commitment to the team. A commitment score for each athlete was calculated by averaging each player's responses to the 4-items, while a commitment score for each team was calculated by aggregating team members' scores to the group-level. Evidence for the factorial and discriminant validity and reliability of the commitment scale has been demonstrated with youth sport participants (Scanlan, Simons, Carpenter, Schmidt, & Keeler, 1993). The sport commitment scale has also been used with an adult sample of university staff and students engaging in exercise classes (Wilson, Rodgers, Carpenter, Hall, Hardy, & Fraser, 2004) and adult rugby players of recreational, amateur, university, and professional clubs (Boardley, Kavussanu, & Ring, 2008). Internal consistency reliabilities for the team commitment scale were .90 at Time 1 and .93 at Time 2.

Social network variables. The network data were collected through a sociometric instrument and measured as complete networks with each participant referring to all other team members when responding to a network item. Complete network analysis obtains all interactions among actors in a group which produces an actor-by-actor matrix of relational values. Data were recorded in the form of an adjacency matrix where each actor was assigned both a column and a row. Athletes and head coaches received an alphabetized list of every team member (including the head coach for athletes) and asked to identify those with whom they shared each kind of relation. The sociometric questionnaire is presented in Appendix F. The communication network item asked participants to rate how frequently they talked with each of their team members on subjects that were related to the team's functioning such as discussing the team's strengths and weaknesses, performances, or goals. Respondents were asked to circle the appropriate number next to each member's name using a scale ranging from 1 (*very little*) to 5 (*a great deal*). The friendship network item asked participants to indicate who they considered to be a very good, someone they saw socially outside of team-related activities. Respondents were asked to place an X next to the names of each team member who they considered a friend. For the friendship item, participants were allowed to select as many members as applicable.

Structural density is the ratio between the number of ties in a network and the total number of possible ties in a network. Because directed relations were assessed (e.g., Person A might indicate that Person B was a friend, but Person B might not indicate that Person A is a friend), density was calculated by the equation: $l/n(n-1)$, where l was the number of lines present and n was the number of actors within the network. The density coefficient can range from 0 *(no density)* to 1 *(complete density)*. A binary format was used to calculate network density. Because the communication scale was value-based, the ratings were dichotomized. Ratings of 1, 2, and 3 received a value of 0, while ratings of 4 and 5 received a value of 1. Ucinet software was used to compute the density coefficient for each team (Borgatti, Everett, & Freeman, 2002).

Network centralization is the sum of the differences between the largest centrality score and all other observed centrality scores, divided by the maximum possible sum of differences in actor centrality (Wasserman & Faust, 1994). Centralization was calculated using Freeman's (1979) degree-based centralization index:

$$C_D = \sum [C_D(n^*) - C_D(n_i)] / (g-1)^2,$$

where $C_D(n^*)$ is the centrality of the most central node, $C_D(n_i)$ is the centrality of actor i, and g is the number of actors. Because relations were measured as directional, the denominator was $(g-1)^2$ instead of $(g-1)$ x $(g-2)$. The centralization score can range from

0 (every member is connected to every other member) to 1 (all members are connected to only 1 member). Ucinet software was used to compute the centralization coefficient for each team (Borgatti et al., 2002).

Team performance. Team performance was conceptualized as a team's winning percentage and was calculated by dividing the number of wins by the number of games a team had played. It is a standardized measure that takes into account the number of games a team had played prior to completing the self-report questionnaires. Win/loss records for each team were obtained from the head coach and verified through team and conference websites.

Run differential. Although winning and losing are absolute measures of team performance, winning percentage may not necessarily be the best method of assessing how well a team performs because not all wins and losses are equal. For instance, losing by one run is seemingly better than losing by ten runs. Thus, in addition to winning percentage, run differential was calculated for all teams by subtracting the number of runs allowed from the number of runs scored. This score was divided by the number of games played to produce a run differential per game score because certain teams played a different number of competitions than other teams. The number of runs scored and runs allowed for each team were obtained from team and conference websites.

Team size. The number of players on a team can affect group level social network metrics such as density. Therefore, Friedkin (1981) recommends that group size and density should be analyzed simultaneously. Team size may also influence perceptions of collective efficacy. According to Zaccaro et al. (1995), teams with more members may have higher perceptions of collective efficacy because there are greater amounts of resources available in larger groups. Conversely, team size may be negatively related to collective efficacy because coordination becomes more difficult and the likelihood of social loafing and clique formation increases as the size of the group increases. Consequently, team size was assessed to examine relationships between network variables and collective efficacy dispersion. Team size was measured as the total number of players on a given team as reported by the coach and was verified through team rosters.

Data Analyses

Descriptive statistics (i.e., mean, standard deviation) and bivariate correlations were calculated for all variables. Internal consistency reliabilities were computed for scales that had multiple items.

A multiple regression was run to test Hypotheses 1-6 (i.e., communication density, friendship density, communication centralization, friendship centralization, communication subgroup, and friendship subgroup). Confidence in the coach was included as a predictor variable in the preliminary model, but it was unrelated to collective efficacy dispersion and thus, was removed from the final model. Collective efficacy dispersion at Time 2 was regressed on collective efficacy dispersion at Time 1 and the six network variables. To test Hypothesis 7 (the moderating influence of dispersion on the relationship between collective efficacy and team performance), a multiple regression was run at two time points (middle of the season and end of the season). For instance, middle of the season winning percentage was regressed on collective efficacy, dispersion, and the interaction between collective efficacy and dispersion assessed at the beginning of the season. Similar analyses were conducted for run differential. The collective efficacy and dispersion variables were centered to reduce multicollinearity with the interaction term. Similarly, Hypothesis 8 (the moderating influence of dispersion on the relationship between collective efficacy and team commitment) was tested using multiple regression analyses with centered collective efficacy, centered dispersion, and the collective efficacy by dispersion interaction as the independent variables. Separate analyses were conducted for team commitment at Time 1 and Time 2. Because the team commitment scale was significantly skewed at both time points, a negative base-10 logarithm was applied in order to normalize the distributions.

Research Questions 1 and 2 pertain to the occurrence of subgroups within teams. In order to identify non-overlapping subgroups based on communication and friendship ties within teams, Klique Finder was used. Klique Finder is based on Frank's (1995, 1996) network clustering algorithm and determines whether there is evidence that actors engage in exchanges within subgroups at a rate that is unlikely to have occurred by chance alone. To test for subgroup processes, a likelihood ratio test between two models is compared: 1) Log $(p[w_{ii'} = 1]/1\text{-}p[w_{ii'} = 1]) = \Theta_0 + \Theta_{1base}\, same\ group_{ii'}$ and 2) Log $(p[w_{ii'}=1]/1\text{-}p[w_{ii'}=1]) = \Theta_0 + \Theta_{1base}\, same\ group_{ii'} + \Theta_{1subgroup\ processes}\, same\ group_{ii'}$. A small p-value indicates that the null hypothesis that $\Theta_{1subgroup\ processes}$ is zero can be rejected, which provides evidence that there are subgroups based on interaction patterns. Using the approximate test of concentration of ties within subgroups based on the size of $\Theta_{1subgroup\ processes}$, each team was examined separately to determine whether it contained subgroups. This analysis was performed for both communication and friendship ties. A dichotomous variable was created where teams with subgroups were coded as 1, while teams without subgroups were coded as 0.

Research Questions 3 and 4 relate to whether subgroups align by collective efficacy, while Research Questions 5 and 6 relate to whether individuals' collective efficacy beliefs are influenced by members of their communication and friendship subgroup. Based on the Klique Finder results, only teams that demonstrated evidence of subgroups were included in the analyses examining these research questions. Because of the nested nature of the data (i.e., individuals within subgroups within teams), multilevel modeling was used. Multilevel statistical techniques (e.g., hierarchical linear modeling – HLM) reduce the problems associated with single level analyses by enabling the researcher to simultaneously examine relationships at each level and across levels, while determining the amount of variation at each level (Raudenbush & Bryk, 2002). Separate multilevel analyses were conducted for communication and friendship subgroups where collective efficacy at Time 2 was the dependent variable. The first step of model building involved imposing an unconditional model where no individual, subgroup, or team level predictors were entered into the model. The primary purpose of fitting the unconditional model was to determine the amount of variation in collective efficacy that existed at each level (Research Questions 3 and 4). After running the unconditional model, prior levels of collective efficacy were entered as predictors at each level (individual, subgroup, and team) to examine whether collective efficacy beliefs were influenced by subgroup processes (Research Questions 5 and 6). All predictor variables were grand-mean centered. The multilevel model for collective efficacy at Time 2 was:

Level 1:

$$\text{collective efficacy } 2_{icj} = \pi_{0cj} + \pi_{1cj}\text{collective efficacy } 1_{icj} + e_{ijk}$$

Level-2:

$$\pi_{0cj} = \beta_{00j} + \beta_{01j}\text{collective efficacy 1 subgroup mean}_{cj} + r_{0cj}$$

$$\pi_{1cj} = \beta_{10j}$$

Level-3:

$$\beta_{00j} + \gamma_{000} + \gamma_{001}\text{collective efficacy 1 team mean}_{j} + u_{00j}$$

$$\beta_{01j} = \gamma_{010}$$

$$\beta_{10j} = \gamma_{100}$$

CHAPTER 4

RESULTS

Descriptives

Descriptive statistics pertaining to athlete and coach demographics are presented in Table 1 and Table 2, respectively. Means and standard deviations for selected team level variables are presented in Table 3. Collective efficacy scores ranged from 3.38 to 4.64 (M = 3.89, SD = .32) at Time 1 and from 2.95 to 4.79 (M = 3.82, SD = .41) at Time 2. Dispersion scores ranged from -.28 to -.01 (M = -.15, SD = .05) at Time 1 and from -.44 to .00 (M = -.17, SD = .07) at Time 2. Team commitment scores ranged from 3.52 to 5.00 (M = 4.74, SD = .25) at Time 1 and from 3.44 to 5.00 at Time 2. Confidence in the coach scores ranged from 2.27 to 4.98 (M = 3.94, SD = .64). For the social network variables, teams tended to have moderately dense communication networks (M = .47, SD = .11) and friendship networks (M = .65, SD = .12), and more decentralized communication (M = .19, SD = .05) and friendship (M = .26. SD = .08) networks. Klique Finder identified 15 (32.6%) teams that had communication subgroups and 13 (28.3%) teams that had friendship subgroups. Each communication subgroup contained 3 to 14 members, whereas each friendship subgroup contained 3 to 16 members. Similar to the multilevel analysis procedures described in the data analyses section of Chapter 3, an unconditional model was run with years on the team as the outcome variable to determine if subgroups aligned by number of years on team. Results revealed that 34% of the variance was due to communication subgroup membership ($p < .001$), whereas 32% of the variance was due to friendship subgroup membership ($p < .001$). Thus, subgroups tended to align by number of years on the team. In addition, a χ^2 test of independence was conducted to determine whether subgroups also aligned by starting status (starter, non-starter). Results revealed that communication subgroups aligned by starting status ($p < .01$), but friendship subgroups did not.

Bivariate correlations for selected team level variables are presented in Table 4. Pearson Product Moment correlations revealed that collective efficacy was significantly and positively related to team performance and run differential. In addition, there was a significant and positive relationship between collective efficacy and team commitment at both time points. Collective efficacy was significantly and negatively associated with dispersion with stronger correlations occurring at similar time points (e.g., Collective Efficacy 1 and Dispersion 1; Collective Efficacy 2 and Dispersion 2). Interestingly, the correlation between Dispersion 1 and Dispersion 2 ($r = .56$) was weaker than the correlation between Collective Efficacy 1 and Collective Efficacy 2 ($r = .77$), indicating that collective efficacy dispersion was less stable over time. There was a significant and negative correlation between dispersion and team performance, as well as dispersion and run differential. For relationships between dispersion and team commitment, only Dispersion 2 and Team Commitment 2 were significantly related. Confidence in the coach was significantly and negatively associated with collective efficacy dispersion. Although modest correlations were found between the network variables and dispersion, only communication subgroup was significantly associated. There was a significant and negative relationship between friendship centralization and collective efficacy at Time 1 and 2. Low to moderate correlations were found between the network measures, with significant correlations ranging from .36 to .65.

Bivariate correlations between team level demographic variables, dispersion, and network variables were also performed to determine whether certain demographic variables should be included as control variables in subsequent analyses. Team size and mean years on the team did not significantly correlate with dispersion or any of the social network variables.

For the sociometric questionnaire, team response rates ranged from 65% to 100% (M = 96%, SD = .07) with 27 teams (59%) providing complete data. Consensus estimates were performed for all variables that were aggregated to the team level. Estimates were calculated across the items of each scale using the within-group interrater agreement index, r_{wg}, (James et al., 1984), assuming no response bias and discrete data. The number of response categories for collective efficacy, team commitment, and confidence in the coach met the discrete assumption of seven plus or minus two (James et al., 1984). R_{wg} values for collective efficacy ranged from .75 to .89 (M = .82, SD = .03) at Time 1 and from .75 to .91 (M = .83, SD = .04) at Time 2. For team commitment, r_{wg} values ranged from .76 to 1.24 (M = .90, SD = .09) at Time 1 and from .76 to 1.16 (M = .86, SD = .09) at Time 2. R_{wg} values for confidence in the coach ranged from .75 to .99 (M = .81, SD = .06). Furthermore, correlations between r_{wg} and SD for collective efficacy beliefs were -.99 at Time 1 and -.97 at Time 2, indicating that the choice of dispersion index was inconsequential.

Social Network Variables and Dispersion

Hypotheses 1-6 posit that network variables influence collective efficacy dispersion, while controlling for prior levels of collective efficacy dispersion. To test these hypotheses, dispersion at Time 2 was regressed on dispersion at Time 1, communication density, friendship density, communication centralization, friendship centralization, communication subgroup, and friendship subgroup. Results are presented in Table 5. Prior collective efficacy dispersion significantly predicted dispersion at Time 2 (β = .49, $p < .001$). For the network variables, communication and friendship density, as well as friendship centralization did not significantly predict collective efficacy dispersion. Thus, Hypotheses 1, 2, and 4 were not supported. However, the influence of communication centralization on collective efficacy dispersion (Hypothesis 3) approached statistical significance (β = .22, p = .08), indicating that teams with less centralized communication networks had lower levels of collective efficacy dispersion than teams with more centralized communication networks. Subgroups based on communication and friendship ties demonstrated significant, but differential effects. Communication subgroups were a significant and positive predictor of dispersion (β = .45, $p < .01$), whereas friendship subgroups were a significant and negative predictor of dispersion (β = -.31, $p < .05$). Thus, Hypothesis 5 was supported and Hypothesis 6 was in the unexpected direction. Teams with communication subgroups had higher levels of dispersion, while teams with friendship subgroups had lower levels of dispersion. The regression model explained 43% of the variance in collective efficacy dispersion at Time 2 (ΔR^2 = .20, *F change* = 2.66, $p < .05$).

Multilevel Model of Collective Efficacy Based on Subgroups

In order to determine the amount of variation in collective efficacy that existed at the subgroup level (Research Questions 3 and 4) and to examine whether collective efficacy beliefs were influenced by subgroup's prior mean levels of collective efficacy

(Research Questions 5 and 6), multilevel modeling was used. As discussed in the method section, separate multilevel analyses were conducted for communication and friendship subgroups, respectively. For the multilevel model of collective efficacy based on communication subgroups, there were 274 individuals within 47 subgroups within 15 teams. Results from the unconditional model revealed that 62% of the variance in collective efficacy was at the individual level, 5% was at the subgroup level, and 33% was at the team level. While only 5% of the variance was due to communication subgroup membership, the variance component was significant ($\chi^2 = 46.78$, $p < .05$), providing some support that communication subgroup membership was related to collective efficacy beliefs. After running the unconditional model, collective efficacy at Time 1 was included as a predictor variable at each level of analysis to examine whether collective efficacy beliefs at Time 2 were influenced by subgroup's prior mean level of collective efficacy. That is, collective efficacy at Time 2 was predicted by individuals' prior collective efficacy, subgroups' prior collective efficacy, and teams' prior collective efficacy. Results from the multilevel model based on communication subgroups are presented in Table 6. Prior collective efficacy at the individual ($\beta = .57$, $p < .001$) and team ($\beta = .62$, $p < .05$) level were significant and positive predictors of collective efficacy at Time 2. However, subgroup's prior mean level of collective efficacy did not predict collective efficacy at Time 2, after controlling for prior levels of collective efficacy at the individual and team level.

Similar analyses were performed for friendship subgroups. For the multilevel model of collective efficacy based on friendship subgroups, there were 204 individuals within 30 subgroups within 13 teams. Results from the unconditional model revealed that 51% of the variance in collective efficacy was at the individual level, 13% was at the subgroup level, and 36 % was at the team level. The variance component associated with friendship subgroups was significant ($\chi^2 = 42.65$, $p < .01$), providing support that friendship subgroup membership was related to collective efficacy beliefs. Results from the multilevel model based on friendship subgroups with prior levels of collective efficacy included at each level are presented in Table 7. Prior collective efficacy at the individual level was a significant and positive predictor of collective efficacy at Time 2 ($\beta = .43$, $p < .001$), while prior collective efficacy at the team level was unrelated to collective efficacy at Time 2. Further, the influence of subgroups' prior mean levels of collective efficacy approached statistical significance ($\beta = .25$, $p = .13$).

Moderating Influence of Dispersion on Team Performance

To test whether dispersion moderated the relationship between collective efficacy and team performance (Hypothesis 7), a regression was run for each time point (Collective Efficacy 1 and Team Performance 2/Run Differential 2; Collective Efficacy 2 and Team Performance 3/Run Differential 3). In order to reduce multicollinearity, the predictors (collective efficacy, dispersion, and the collective efficacy by dispersion interaction) were centered. The results of the regression analyses are presented in Table 8. For Team Performance 2 and 3, the collective efficacy by dispersion interaction was not significant, indicating that dispersion did not moderate the relationship between collective efficacy and team performance. Instead, collective efficacy was the sole predictor of Team Performance 2 ($\beta = .55$, $p < .01$) and 3 ($\beta = .67$, $p < .001$). The regression models for Team Performance 2 and 3 accounted for 32% and 58% of the variance, respectively. For Run Differential 3, Collective Efficacy 2 was a significant and positive predictor ($\beta = .57, p < .001$). Furthermore, collective efficacy dispersion emerged as a significant predictor ($\beta = -.31, p < .05$) of run differential, while the collective efficacy by dispersion interaction approach statistical significance ($\beta = .22, p = .08$). Thus, Hypothesis 7 was partially supported, though in the unexpected direction. The model for Run Differential 3 explained 52% of the variance.

Moderating Influence of Dispersion on Team Commitment

To test whether dispersion moderated the relationship between collective efficacy and team commitment (Hypothesis 8), a regression was run for each time point (Collective Efficacy 1 and Team Commitment 1; Collective Efficacy 2 and Team Commitment 2). Similar to the team performance/run differential regression analyses, the predictors (collective efficacy, dispersion, and the collective efficacy by dispersion interaction) were centered to reduce multicollinearity. The results of the regression analyses are presented in Table 9. For Team Commitment 1 and 2, the collective efficacy by dispersion interaction was not significant, indicating that dispersion did not moderate the relationship between collective efficacy and team commitment. Thus, Hypothesis 8 was not supported. Instead, collective efficacy was the sole predictor of Team Commitment 1 ($\beta = .43, p < .05$) and 2 ($\beta = .55, p < .01$). The regression models explained 14% and 43% of the variance in team commitment, respectively.

Summary of Hypotheses and Results

Hypotheses 1-6 investigated the influence of social network variables on collective efficacy dispersion, while controlling for prior levels of collective efficacy dispersion. Hypothesis 1 posited that communication density would be negatively related to collective efficacy dispersion. No support was found for Hypothesis 1.

Hypothesis 2 posited that friendship density would be negatively related to collective efficacy dispersion. No support was found for Hypothesis 2. Hypothesis 3 was that communication centralization would be positively related to collective efficacy dispersion. Partial support was found for Hypothesis 3 in that the influence of communication centralization approached statistical significance. Hypothesis 4 was that friendship centralization would be negatively related to collective efficacy dispersion. No support was found for Hypothesis 4. Hypothesis 5 posited that friendship subgroups would be positively related to collective efficacy dispersion. Although statistically significant, the influence of friendship subgroups was in the unexpected direction. Hypothesis 6 posited that communication subgroups would be positively related to collective efficacy dispersion. Support for Hypothesis 6 was found. Hypotheses 7 and 8 examined the moderating influence of collective efficacy dispersion. Hypothesis 7 was that collective efficacy dispersion would moderate the relationship between aggregated collective efficacy and team performance. Partial support was found for Hypothesis 7, though in the unexpected direction. The relationship between aggregated collective efficacy and run differential was stronger for teams with high dispersion. Hypothesis 8 was that collective efficacy dispersion would moderate the relationship between aggregated collective efficacy and team commitment. No support was found for Hypothesis 8.

CHAPTER 5

DISCUSSION

Despite ample research on collective efficacy in sport and organizational psychology, little is known as to why some teams develop more interrelated collective efficacy beliefs over time and others do not, and the further implications this has on team functioning. In this study, a dispersion theory of collective efficacy was developed and investigated by examining the antecedents and moderating influence of collective efficacy dispersion. Theorists have suggested that interaction patterns represented as social networks contribute to the emergence of shared beliefs, and that the relationship between collective efficacy and team-related outcomes depend on the degree of within-team variability surrounding members' judgments. Findings from this study contribute to a better understanding of collective efficacy dispersion. This chapter discusses the findings of the current study, identifies implications of these results, discusses strengths and limitations of the study, and presents future research directions.

The Emergence of Collective Efficacy Dispersion

The novel finding of this study was that subgroups based on communication and friendship ties influenced collective efficacy dispersion, even after controlling for prior levels of dispersion. However, the direction of effect differed for communication and friendship subgroups, respectively. Teams with communication subgroups had members with more dispersed collective efficacy beliefs than teams that did not have communication subgroups. This finding is consistent with the theorizing of Brown et al. (1996) who speculated that dispersion at the group level may result from subgroups based on social interaction. While subgroups create patterns of local agreement, there tends to be collective efficacy dispersion in the team as a whole. In contrast, teams with friendship subgroups had group members with less dispersed collective efficacy beliefs than teams without friendship subgroups. However, this finding appears to be a statistical artifact. When examined separately from communication subgroups, the influence of friendship subgroups on collective efficacy dispersion was not significant. This is further supported by the bivariate correlations presented in Table 4, which demonstrate that there was no relationship between friendship subgroups and collective efficacy dispersion ($r = -.01$).

There was some support for the notion that communication and friendship subgroups aligned according to collective efficacy beliefs. That is, individuals of cohesive subgroups tended to have similar collective efficacy beliefs in that there was a significant amount of variance in collective efficacy at the subgroup level. However, the amount of variance attributed to subgroup membership was rather low (5% for communication subgroups and 13% for friendship subgroups). Further substantiating this point was that individuals' perceptions of collective efficacy were not influenced by their subgroup's prior mean levels of collective efficacy. If subgroup effects were salient in determining collective efficacy, then it would be expected that individuals would conform to their subgroup's normative belief over time as a result of frequent interactions with proximal members. Indeed, a social network approach to subgroups suggests that members of cohesive subgroups develop similar beliefs over time through dense patterns of social interaction. However, results from the current study indicate that collective efficacy may not be a belief that is influenced by subgroup processes.

Perhaps having a small number of teams with the presence of subgroups provided a limited test of subgroup effects.

Although descriptive in nature, an interesting finding was that the majority of teams in this study did not have communication or friendship subgroups. Among the teams that participated in the study ($N = 46$), 15 (33%) teams demonstrated evidence of communication subgroups, while 13 (28%) teams demonstrated evidence of friendship subgroups. Teams that had subgroups were similar to teams that did not have subgroups in terms of coaching demographics (gender, age, years coaching the team, and coaching experience) and division. In addition, the presence of subgroups was not associated with team size, team experience, or team mean number of years on the team. Because subgroups based on social interaction have not been examined in sport, it is difficult to know whether the percentages found are representative of sports teams in general. In comparison to other settings such as schools or business, subgroups may be less common among athletic teams because of increased opportunities for social interaction. For instance, members of competitive sports teams often interact with each other on a daily basis, either at strength training sessions, practice sessions, team meetings, or competitions. The frequent opportunities to communicate and develop personal relationships, which are inherent to team sports, may explain why most teams in this study did not have subgroups. In addition, coaches and team captains try to build team unity intentionally, as exemplified by the popular slogan, "there is no I in team." Another explanation may be that communication and friendship subgroups are more prevalent in different types of sports. For instance, sports characterized by larger team sizes where team members are required to perform specific roles (e.g., football) may be more likely to develop subgroups. Although the majority of teams in this study did not have subgroups, the importance of investigating subgroups was demonstrated in that teams with subgroups had different levels of collective efficacy dispersion than teams without subgroups. Thus, future studies should continue to examine subgroups based on different social relations with athletic teams.

Results from this study provided partial evidence that the structure of communication ties influences the degree of within-team variability in members' collective efficacy beliefs. Teams with more decentralized communication patterns had less collective efficacy dispersion than teams with more centralized communication patterns. This finding is consistent with previous research that suggests decentralized communication networks facilitate the spread of information and promote shared understandings among group members (Cummings & Cross, 2003; Zohar & Tenne-Gazit, 2008). In contrast to centralized communication networks which revolve around a highly central actor, decentralized communication networks offer better social diffusion processes because communication exchanges are unconstrained. Thus, information regarding the team's strengths and weaknesses, performances, and goals is discussed openly among all network members, which contributes to a shared sense of collective efficacy at the team level. Alternatively, in teams with centralized communication structures, central actors have disproportionate access to members' attitudes and beliefs. A centralized communication configuration may produce collective efficacy dispersion because peripheral members' beliefs are isolated, and only the central actor is involved in the majority of discussions about the team's functioning.

The proposed hypotheses related to network density and collective efficacy dispersion were not supported. Teams with dense communication and friendship networks did not have less collective efficacy dispersion than teams with sparse networks. This finding is in contrast to previous research that suggests dense networks promote homogenous perceptions among team members, whereas sparse networks contribute to heterogeneous perceptions among team members (Zohar & Tenne-Gazit, 2008). An explanation for the inconsistent results may be attributed to the analysis used in this study. Previous network studies in organizational psychology have conducted separate analyses for density and centralization, and have employed cross-sectional designs (e.g., Zohar & Tenne-Gazit, 2008). The current investigation simultaneously examined several network variables (e.g., density, centralization, subgroups) and controlled for prior levels of dispersion. When separate analyses are conducted, the independent contributions of the predictor variables (i.e., density and centralization) can not be determined. For instance, Sparrowe and colleagues (2001) found that network density was unrelated to team performance, after accounting for network centralization. Accordingly, in this study, network density did not influence collective efficacy dispersion, beyond the effects of network centralization and subgroups. Findings from this study indicate that the structural patterns of ties (i.e., centralization and subgroups) may be more salient antecedents of collective efficacy dispersion than the magnitude of ties (i.e., density).

Collective Efficacy Dispersion as an Independent and Moderating Variable

The majority of studies that have examined the influence of collective efficacy on team performance have neglected the degree of within-team variability around the group level mean. However, theorists have proposed that within-team variation in members' collective efficacy beliefs moderates the relationship between collective efficacy magnitude and team performance (Gully et al., 2002). This study tested this proposition and found partial support for the moderating influence of collective efficacy dispersion. For midseason and end of the season winning percentage, neither dispersion nor the collective efficacy by dispersion interaction was a significant predictor beyond the magnitude of collective efficacy beliefs. However, teams with less collective efficacy dispersion at the middle of the season outscored their opponents (at the end of the season) to a higher degree than teams with more collective efficacy dispersion, regardless of the magnitude of collective efficacy beliefs. This suggests that in addition to enhancing collective efficacy through sources of efficacy information (i.e., mastery experiences, vicarious experiences, verbal persuasion, and physiological/emotional states), coaches and practitioners should focus on developing shared beliefs among team members. Even when the magnitude of collective efficacy is moderate, teams may benefit by achieving higher levels of agreement. As collective efficacy beliefs become more interrelated, conflict among teammates is reduced, which allows teams to focus on coordinative processes that impact team functioning. Partial evidence was found for collective efficacy dispersion as a moderator of the collective efficacy-run differential relationship. However, the moderating effect was in the unexpected direction. Although the relationship between middle of the season collective efficacy and end of the season run differential was positive for teams with low and high dispersion, the relationship was stronger for teams with higher levels of dispersion. This finding is inconsistent with previous research that found that the relationship between aggregated collective efficacy and team performance was positive only for teams with low dispersion (Arthur et al., 2007) and suggests that the collective efficacy-team performance relationship is robust. Furthermore, this study addressed several of the limitations associated with previous collective efficacy dispersion research. For instance, Arthur and colleagues employed an experimental design with all-male dyads, and used a 2-item collective efficacy questionnaire. This study was conducted in a natural setting with intact women's softball teams comprised of multiple members, and used a 10-item sport-specific measure of collective efficacy. Therefore, findings from the current investigation extend previous research, and provide evidence for the construct validity of collective efficacy dispersion.

In addition to team performance, dispersion was hypothesized to moderate the relationship between collective efficacy and team commitment such that, the association would be stronger when group members' beliefs were more interrelated. However, no support was found for the moderating influence of dispersion, as only collective efficacy magnitude emerged as a significant predictor of team commitment at the beginning of the season and middle of the season. This finding is in contrast to previous dispersion studies that suggest interrelated beliefs foster uniform affective responses such as team commitment (Gonzalez-Roma et al., 2002). An explanation for the inconsistent results may be the sample used in this study. Whereas previous studies have used work units, the current study used softball teams where the majority of athletes reported strong feelings of commitment to their team. As a result, there was little variation between teams. Although a negative base-10 logarithm was applied to the team commitment scale to normalize the distribution, there may not have been enough differences between teams for dispersion to emerge as an important factor beyond the magnitude of collective efficacy. Nevertheless, the finding that teams with stronger collective efficacy beliefs were more committed than teams with weaker collective efficacy beliefs contributes to a fuller understanding regarding the consequences of collective efficacy. While previous studies have investigated the influence of collective efficacy on various team affective states (e.g., Chow & Feltz, 2008; Pescosolido, 2003; Peterson et al., 2000), none have examined team commitment. When members are committed to continue playing with their team, they are more likely to identify with their group and invest time and effort into group endeavors. Thus, team commitment has implications for group cohesion, motivation, and psychological/physical withdrawal. Findings from this study suggest that these factors can be modified by fostering collective efficacy beliefs within teams.

Implications

The current study has demonstrated that not only are aggregated collective efficacy beliefs important, but also the degree of within-team variability in group members' judgments. As team members' collective efficacy beliefs become more similar over time, team performance tends to improve in a linear direction. However, it cannot be assumed that the sources of aggregated collective efficacy extend to collective efficacy dispersion. This study uncovered an underlying mechanism into why some teams develop more interrelated beliefs, while others do not, that is, through the pattern of social interaction. An implication of this finding is that coaches and applied consultants can increase homogenous collective efficacy beliefs within teams by providing opportunities for interpersonal interaction and by focusing on social activities that involve active participation from all team members. Employing activities and techniques that facilitate the spread of information flow such as team goal-setting, where each member discusses her perspective about the team's functioning, should promote shared collective efficacy beliefs at the team level. Misinterpretations of team goals and previous performances may arise when members have limited access to the attitudes and beliefs of others. However, it is important to note that extremely low levels of collective efficacy dispersion may be detrimental to team functioning and performance. When team members hold identical beliefs about the team's functioning, they are less likely to engage in effective decision making processes and reappraise strategies after performance setbacks. Having some doubt, especially in the preparatory stages of performance, may actually increase motivational levels and facilitate the development of skills (Bandura, 1997). Another implication of this study pertains to the coach's role in providing accurate feedback. Although performance outcomes provide a common experience for members to judge the capabilities of their team, coaches are often responsible for framing the results through encouragement and feedback. Coaches who provide inconsistent feedback or only share their perspectives with certain individuals such as assistant coaches or captains are likely to create within-team variation in members' collective efficacy beliefs which in turn, may impair team functioning.

Strengths and Limitations

This study used a social network approach to understand how team members' collective efficacy beliefs become shared or dispersed over time. Scholars have assumed that social interaction underlies consensus formation within teams (Jung & Sosik, 2003), and have recommended that social network techniques be employed to further advance this line of inquiry (Gibson, 1999; Chow & Feltz, 2008). An advantage of social network techniques is that they describe the structure and pattern of social ties within teams, and provide a more comprehensive measure of group interaction than traditional instruments. Indeed, by utilizing a social network approach, I found that the structural configurations of networks (i.e., centralization and subgroups) were more salient in determining collective efficacy dispersion than the mere intensity of social interaction (i.e., density).

Another strength associated with the current investigation pertains to the longitudinal nature of the design. The methodology used in this study improved upon previous dispersion and network studies by accounting for prior levels of dispersion, while examining the influence of social interaction. This limitation was addressed by obtaining an initial measure of collective efficacy at a time point that was constant across all teams (i.e., beginning of the season). Previous organizational research has employed cross-sectional designs, which made it difficult to determine whether social interaction contributed to within-team variability or whether within-team variability contributed to social interaction. By including a prior estimate, I was able to determine that social interaction patterns within teams influenced subsequent levels of collective efficacy dispersion above and beyond initial levels of dispersion.

Although there are several strengths associated with this study, there are some limitations that should be mentioned. The first limitation was the sample size. While the number of teams that participated in this study ($N = 46$) could certainly be considered large for sport psychology research, the sample size was less than ideal for statistical purposes. Small sample sizes are a common problem in group research because a team comprised of several members is essentially reduced to one participant. Some of the proposed hypotheses tested in this study approached statistical significance (e.g., communication centralization and dispersion, collective efficacy by dispersion interaction and run differential). Perhaps these hypotheses would have been supported had there been more teams in the study. In addition, approximately 33% of the teams in this study had subgroups. This significantly reduced the sample size and degrees of freedom in the multilevel model examining whether subgroups aligned by collective efficacy and whether subgroup processes influenced collective efficacy beliefs. Future studies with larger sample sizes may have the power necessary to detect stronger team differences, and should increase the likelihood of identifying a sufficient number of teams with subgroups.

The second limitation of the study pertains to the temporal proximity between collective efficacy and team performance measurement. Studies that have investigated the relationship between collective efficacy and team performance have typically assessed collective efficacy within 24 hr. prior to competition (e.g., Feltz & Lirgg, 1998; Myers, Feltz et al., 2004; Myers, Payment et al., 2004). This line of work has used competition-specific measures of collective efficacy (e.g., How confident are you that your team can perform in the upcoming competition) and has examined its influence on team performance in the competition referenced. An alternative to competition-specific measures of collective efficacy are general measures of collective efficacy. A general sense of collective efficacy focuses on team's beliefs in their coordinative capabilities to perform at certain points in time. General measures have been used in studies that have assessed collective efficacy at multiple time points (e.g., Paskevich et al., 1999; Watson et al., 2001), rather than studies that have assessed collective efficacy prior to all competitions throughout a season (e.g., Feltz & Lirgg, 1998; Myers, Feltz et al., 2004; Myers, Payment et al., 2004). Because measures of collective efficacy could not be obtained prior to each competition, a general measure was used in this study. As a result, findings related to the moderating influence of collective efficacy dispersion on team performance may be limited. Although competition-specific measures are recommended in collective efficacy-team performance research (Myers & Feltz, 2007), the regression models in this study explained between 32% and 58% of the variance in team performance. However, a better understanding of the moderating influence of collective efficacy dispersion could be achieved by assessing collective efficacy prior to selected competitions.

A final limitation of the current investigation was that complete networks were not assessed. In this study, a social network was defined as the players and head coach within the team. However, not only are teams comprised of players and head coaches, but also trainers and assistant coaches. By not including these individuals as part of the social network, it was assumed that the interactions of players and head coaches with trainers and assistant coaches were constant. This assumption is problematic because certain players are likely to have different social interactions with trainers and assistant coaches. For purposes of this study however, it would have been difficult to assess the complete network of relationships within teams. Unlike players and head coaches, trainers and assistant coaches are not always listed on team rosters. Furthermore, the number of trainers and assistant coaches significantly varies between teams. Thus, the current study focused on the most visible and perhaps relevant members of the social system. Future studies could address this limitation by examining the social ties that occur among all individuals on the team.

Future Research Directions

Because this study represents an initial attempt to examine the antecedents and moderating influences of collective efficacy dispersion, there are several areas that could be investigated in future studies. First, the current study focused on the degree of collective efficacy dispersion as measured by within-team variability (i.e., *SD*). However, DeRue et al. (in press) have proposed that in addition to the degree of within-team variation, the pattern or form of efficacy dispersion should be considered. They suggest that there are four forms of collective efficacy dispersion that may exist within teams, which differentially affect team processes and effectiveness. The first is a shared efficacy configuration which is similar to the conceptualization of previous collective efficacy research, and reflects a general lack of variability among team members' beliefs. A second form is minority dissent where a single team member has a meaningfully different belief relative to the rest of the team. Theoretically, the dissenting member can have a relatively higher or lower collective efficacy belief than the rest of the team. The third is a bimodal form of dispersion which represents a distribution of beliefs along which subgroups form within the team. Finally, a fragmented form of dispersion is where all team members have meaningfully different beliefs. Future researchers could examine whether the forms of collective efficacy dispersion proposed by DeRue and colleagues actually exist in intact groups such as athletic teams. If such configurations are found to exist, then researchers could examine the conditions under which they develop, the factors that create the different forms of dispersion, and the team-related consequences of various efficacy patterns. The various forms of collective efficacy dispersion proposed by DeRue and colleagues were based on 4-person teams, which made it difficult to detect these forms with the data in this study because of the relatively large number of players within teams. Future studies interested in the forms of collective efficacy dispersion should sample teams that are smaller in size such as basketball teams of starters, 4-man bobsled teams, or curling teams. A suggestion related to the DeRue et al. study is that researchers should continue to examine different measurement procedures for assessing various forms of dispersion. For instance, although DeRue and colleagues recommend that skewness and kurtosis estimates be used as measures of efficacy dispersion, recent research suggests that there are several problems associated with these measures (Chow, Dithurbide, & Feltz, 2009).

In order to more fully understand how social networks develop and their effects on group processes, team emergent motivational states, and team functioning, future studies could assess social networks at multiple time points over the course of a competitive season. Due to the time consuming nature of sociometric questionnaires, social network data was collected at only one time point in this study (middle of the season). Thus, it is unknown whether communication and friendship ties within teams at the middle of the season were similar or different from those at the beginning of the season or at the end of the season. Further, an advantage of using intercollegiate sports teams in future social network research is that players' social interactions could be assessed throughout their tenure with the team to examine how these interactions develop or change over time. Intercollegiate athletics provides a context where new members are constantly entering and old members are constantly leaving and as a result, social interactions and relationships within teams are likely to change.

Another future research direction involves using qualitative methods to examine the pattern of social ties within teams. An interesting finding of the current study was that most teams did not have subgroups. However, the teams that demonstrated evidence of communication subgroups had higher levels of collective efficacy dispersion. In order to understand why some teams develop subgroups, while other teams do not, a researcher could follow select teams over the course of a competitive season and conduct interviews or focus groups with players and coaches. Further, qualitative methods may provide further insight into how individuals define communication and friendship ties and whether they are aware of the social structure that exists within the team.

Future studies could also examine other antecedents of collective efficacy dispersion. Understanding the factors that contribute to shared or dispersed collective efficacy beliefs is critical for construct development. Additionally, if further evidence is provided that collective efficacy dispersion predicts important team-related outcomes, then it is imperative that researchers understand how to foster its development and maintenance. This study focused on social interaction as the basis for why teams develop different levels of agreement, though there are certainly other factors that are likely to affect the extent to which members agree about the team's capabilities to be successful. For instance, the stage of group development may impact collective efficacy dispersion. Previous research has indicated that collective efficacy beliefs become more homogeneous over time (Jung & Sosik, 2003), which suggests that levels of dispersion may be more susceptible to change during earlier stages of team development such as the beginning of the season. Examining the factors that contribute to a quick development of interrelated collective efficacy beliefs would be particularly beneficial to coaches and applied consultants. Characteristics of the coach may be another antecedent of collective efficacy dispersion. Leaders who foster close relationships with players, create more opportunities for sharing and clarifying perceptions, and exhibit greater consistency across situations should have teams with less collective efficacy dispersion. In contrast, leaders who create social factions by favoring certain players, employ an autocratic approach to coaching where player input is limited, and provide inconsistent feedback are likely to have teams with dispersed collective efficacy beliefs. Further, there is some evidence of gender differences between male and female coaches of female teams regarding the relationship between coaches' perceptions of motivation efficacy and team satisfaction with male coaches showing no relationship and female coaches showing a significant and positive relationship (Myers, Vargas-Tonsing, & Feltz, 2005). This gender difference in coaching efficacy could influence collective efficacy dispersion.

A final recommendation for future research is to examine gender differences in social interaction patterns. For instance, there may be different communication and friendship dynamics along gender lines. Research has found that females tend to view affectively oriented communication skills as more important, whereas males tend to view instrumentally oriented communication skills as more important (Burleson, Kunkel, Samter, & Werking, 1996). The current study examined women's teams and thus, it is unknown whether the findings generalize to men's teams. In order to investigate gender differences, researchers could compare men's and women's athletic teams in sports that are played by both sexes with similar rules such as soccer, volleyball, or basketball. Comparing women's softball teams with men's baseball teams would provide an inaccurate test because the strategies and rules associated with each sport are fundamentally different.

Conclusions

Although collective efficacy is characterized by both a representative team estimate and the degree of within-team variability around this central belief, previous studies have treated the degree of within-team variability as a statistical precondition for aggregation. In accordance with dispersion theorists (Brown et al., 1996; Chan, 1998), a dispersion theory of collective efficacy was developed and tested with intercollegiate women's softball teams. This study contributes to a better understanding of how the construct emerges and provides support for conceptualizing collective efficacy dispersion as a meaningful group level variable. Social network techniques were used to describe the structure of social interactions within teams, which explained why some teams developed more interrelated collective efficacy beliefs than other teams. In addition, collective efficacy dispersion predicted run differential and moderated the relationship between collective efficacy and run differential.

Appendix A

Athlete Demographic Questionnaire (Time 1)

1. Name (Last, First): ______________________________

2. Today's Date: ________

3. Age: ________

4. College Attended: ______________________________

5. NCAA Division: ________

6. Year in School:
   - ☐ First-Year
   - ☐ Sophomore
   - ☐ Junior
   - ☐ Senior
   - ☐ Fifth-Year

7. Total number of years playing this sport: ________

Answer the following questions regarding the **current season only:**

8. Current position(s) played: __________________________

9. Jersey number: ________

10. Number of years on this team (including this year): ________

11. Are you typically a: ☐ STARTER ☐ NON-STARTER ☐ N/A

12. Are you a team captain this year? ☐ YES ☐ NO

13. Do you consider yourself to be a leader on this team? ☐ YES ☐ NO

Appendix B

Athlete Demographic Questionnaire (Time 2)

1. Name (Last, First): ______________________________________

2. Today's Date: __________

3. Age: __________

4. Year in School:
   - ☐ First-Year
   - ☐ Sophomore
   - ☐ Junior
   - ☐ Senior
   - ☐ Fifth-Year

5. Total number of years playing this sport: __________

Answer the following questions regarding the **current season only:**

6. Current position(s) played: ________________________________

7. Number of years on this team (including this year): __________

8. Are you typically a: ☐ STARTER ☐ NON-STARTER ☐N/A

9. Are you a team captain this year? ☐ YES ☐ NO

10. If not a captain, do you consider yourself to be a leader on this team? ☐ YES ☐ NO

11. How certain are you that **YOUR COACH CAN** communicate effectively with players?

Cannot do at all		Moderately can do		Highly certain can do
1	2	3	4	5

12. How certain are you that **YOUR COACH CAN** build the mental skills of players?

Cannot do at all		Moderately can do		Highly certain can do
1	2	3	4	5

13. How certain are you that **YOUR COACH CAN** make critical coaching decisions?

Cannot do at all		Moderately can do		Highly certain can do
1	2	3	4	5

Appendix C

Coach Demographic Questionnaire

1. Today's Date: __________

2. Gender: ☐ Female ☐ Male

3. Age: __________

4. College currently coaching at: ______________________________

5. Number of years as coach of this team (including this year): __________

6. Total number of years coaching this sport: __________

7. Number of years playing experience in this sport: __________

8. Highest level of playing experience: _________________________

9. What is your team's current (W-L) record: ______________

10. How would you rate the physical ability of the athletes on your team this year?

Very poor				Excellent
1	2	3	4	5

11. How would you rate the teamwork ability of the athletes on your team this year?

Very poor				Excellent
1	2	3	4	5

12. How would you rate the overall ability of the teams on your schedule this year?

Very poor				Excellent
1	2	3	4	5

Appendix D

Collective Efficacy Questionnaire

Directions: Listed below are different team performance skills. Please rate how certain you are that **YOUR TEAM AS A WHOLE** can execute these skills. Circle the appropriate number to the right of **each** statement.

Rate your degree of confidence by recording a number from 1 to 5 using the scale given below:

How certain are you that YOUR TEAM CAN.....

	Cannot do at all		**Moderately can do**		**Highly certain can do**
1. communicate well as a unit	1	2	3	4	5
2. regain mental focus after an error/mistake	1	2	3	4	5
3. avoid walking opposing batters	1	2	3	4	5
4. consistently throw strikes	1	2	3	4	5
5. outscore opponents	1	2	3	4	5
6. consistently put the ball in play	1	2	3	4	5
7. have a high fielding percentage	1	2	3	4	5
8. hit with runners in scoring position	1	2	3	4	5
9. successfully lay down bunts	1	2	3	4	5
10. make good decisions on the base paths	1	2	3	4	5

Appendix E

Team Commitment Questionnaire

Directions: Think about the current season and playing with this team. Please rate how true each statement is to you by recording a number from 1 to 5 using the scale given below. Circle the appropriate number to the right of **each** statement.

	Not at all true for me				**Completely true for me**
1. I am dedicated to playing with this team.	1	2	3	4	5
2. It would be hard for me to quit playing with this team.	1	2	3	4	5
3. I am determined to keep playing with this team.	1	2	3	4	5
4. I am willing to do almost anything to keep playing with this team.	1	2	3	4	5

Appendix F

Social Interaction Questionnaire

Directions: Think about the interactions that you have with other members on this team **in the current season**.

1. Please rate how frequently you talk with each of your team members on subjects that are related to the team's functioning **such as discussing the team's strengths and weaknesses, performances, or goals**. Circle the appropriate number next to **each** member's name in the **talk about team's functioning column**.

2. Place an **X** in the **friend column** next to each member's name who you consider to be **a very good friend of yours, someone whom you see socially outside of team-related activities**. You may select as many members as applicable.

	Talk about Team's Functioning (circle appropriate number for each member, except for yourself)					**Friend** (select as many as applicable)
Player	**Very little**		**Sometimes**		**A great deal**	
EXAMPLE	**1**	**2**	**3**	**4**	**5**	**X**
Player 1	1	2	3	4	5	
Player 2	1	2	3	4	5	
Player 3	1	2	3	4	5	
Player 4	1	2	3	4	5	
Player 5	1	2	3	4	5	
Player 6	1	2	3	4	5	
Player 7	1	2	3	4	5	
Player 8	1	2	3	4	5	
Player 9	1	2	3	4	5	
Player 10	1	2	3	4	5	
Player 11	1	2	3	4	5	
Player 12	1	2	3	4	5	
Player 13	1	2	3	4	5	
Player 14	1	2	3	4	5	
Coach	1	2	3	4	5	

Table 1

Athlete Demographics (N = 763)

Variable	Frequency	*M*	*SD*
Year in School		2.25	1.13
Freshman	255		
Sophomore	214		
Junior	152		
Senior	132		
Fifth-Year	10		
Years on Team		2.09	1.08
One	297		
Two	217		
Three	135		
Four	112		
Five	2		
Starter Status			
Starters	482		
Non-Starters	247		
N/A	34		
Captain Status			
Captain	101		
Non-Captain	662		
Leader Status			
Leader	513		
Non-Leader	250		
Age		19.79	1.30
Playing Experience		12.20	3.49

Table 2

Coach Demographics (N = 46)

Variable	Frequency	*M*	*SD*
Gender			
Female	38		
Male	8		
Years Coaching Team		8.37	7.56
Age		39.58	11.94
Coaching Experience		14.09	9.26
Playing Experience		17.04	8.53

Table 3

Means and Standard Deviations for Team Variables (N = 46)

Variable	*M*	*SD*
Collective Efficacy 1	3.89	.32
Collective Efficacy 2	3.82	.41
Dispersion 1	-0.15	.05
Dispersion 2	-0.17	.08
Communication Density	0.47	.11
Friendship Density	0.65	.12
Communication Centralization	0.19	.05
Friendship Centralization	0.26	.08
Communication Subgroup	0.33	.47
Friendship Subgroup	0.28	.46
Performance 2	0.55	.20
Performance 3	0.55	.18
Run Differential 2	0.87	2.80
Run Differential 3	0.88	2.46
Team Commitment 1	4.74	.25
Team Commitment 2	4.56	.35
Confidence in Coach	3.94	.64

Table 4

Bivariate Correlations for Team Variables (N = 46)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. CE 1	—															
2. CE 2	.77**	—														
3. SD 1	-.53**	-.51**	—													
4. SD 2	-.51**	-.68**	.56**	—												
5. CD	-.02	.09	-.12	-.18	—											
6. FD	.28	.23	-.09	-.20	.49**	—										
7. CC	.04	-.12	.02	.23	-.38*	-.23	—									
8. FC	-.38**	-.32*	.17	.26	-.36*	-.65**	.23	—								
9. CSG	.07	-.15	.16	.31*	-.04	-.03	-.08	-.17	—							
10. FSG	.03	-.03	.12	-.01	.14	-.14	-.08	.06	.49**	—						
11. Per. 2	.60**	.78**	-.39**	-.64**	-.05	.04	-.08	-.17	-.12	-.08	—					
12. Per. 3	.60**	.77**	-.35*	-.60**	-.13	-.06	-.03	-.16	-.09	-.07	.93**	—				
13. RD 2	.58**	.71**	-.42**	-.63**	-.07	-.08	-.07	-.10	-.05	.00	.93**	.88**	—			
14. RD 3	.57**	.70**	-.37*	-.59**	-.16	-.17	.00	-.08	-.07	-.01	.87**	.94**	.94**	—		
15. TC 1	.39**	.43**	-.26	-.29	.17	.31*	.20	-.38**	-.13	-.11	.33*	.39**	.28	.33*	—	
16. TC 2	.43**	.58**	-.23	-.45**	.25	.35*	-.14	-.43**	-.13	-.03	.37*	.41**	.31*	.35*	.66**	—
17. CC	.39**	.72**	-.33*	-.47**	.38**	.31*	-.33*	-.30*	-.13	.01	.47**	.48**	.41**	.42**	.41*	.73**

Note. CE = Collective Efficacy. SD = Collective Efficacy Dispersion. CD = Communication Density. FD = Friendship Density. CC = Communication Centralization. FC = Friendship Centralization. CSG = Communication Subgroup. FSG = Friendship Subgroup. Per. = Team Performance. RD = Run Differential. TC = Team Commitment. CC = Confidence in Coach. *$p < .05$. ** $p < .01$.

Table 5

Dispersion Regressed on Network Variables

Variable	*B*	*SE B*	*β*
Constant	-0.203	0.111	
Dispersion 1	0.777	0.188	0.487***
Communication Density	0.090	0.101	0.127
Freindship Density	-0.022	0.101	-0.036
Communication Centralization	0.003	0.002	0.220
Friendship Centralization	0.002	0.001	0.244
Communication Subgroup	0.071	0.022	0.445**
Friendship Subgroup	-0.051	0.023	-0.307*

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 6

Multilevel Model Based on Communication Subgroups

Fixed Effect	Coefficient	*SE*	*t*
Intercept	3.71	.04	82.85***
CE1 Team	.62	.21	2.92*
CE1 Subgroup	-.05	.15	-.33
CE1 Individual	.57	.06	9.89***
Random Effect	Variance Component	*df*	χ^2
Intercept 1	.01	31	46.28*
Level-1	.16		
Intercept1/Intercept 2	.02	13	35.39**

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 7

Multilevel Model Based on Friendship Subgroups

Fixed Effect	Coefficient	*SE*	*T*
Intercept	3.80	.08	47.36***
CE1 Team	-.09	.26	-.32
CE1 Subgroup	.25	.16	1.57
CE1 Individual	.43	.06	7.34***
Random Effect	Variance Component	*df*	χ^2
Intercept 1	.01	16	22.28
Level-1	.12		
Intercept1/Intercept 2	.07	11	85.13***

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 8

Dispersion as a Moderator of Collective Efficacy-Team Performance Relationship

	β	R^2
DV: Team Performance 2		
Collective Efficacy 1	.55**	
Dispersion 1	-.10	
Collective Efficacy x Dispersion	.03	.32***
DV: Team Perfomance 3		
Collective Efficacy 2	.67***	
Dispersion 2	-.20	
Collective Efficacy x Dispersion	.10	.58***
DV: Run Differential 2		
Collective Efficacy 1	.52**	
Dispersion 1	-.16	
Collective Efficacy x Dispersion	.06	.31***
DV: Run Differential 3		
Collective Efficacy 2	.57***	
Dispersion 2	-.31*	
Collective Efficacy x Dispersion	.22	.52***

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 9

Dispersion as a Moderator of Collective Efficacy-Team Commitment Relationship

	β	R^2
DV: Team Commitment 1		
Collective Efficacy 1	.43*	
Dispersion 1	-.09	
Collective Efficacy x Dispersion	.16	.14*
DV: Team Commitment 2		
Collective Efficacy 2	.55**	
Dispersion 2	-.19	
Collective Efficacy x Dispersion	.03	.43***

*$p < .05$. **$p < .01$. ***$p < .001$.

Figure 1

Example Data of Dispersion

ID	CE1	CE2	CE3	CE4	CE5	*M*	ID	CE1	CE2	CE3	CE4	CE5	*M*
1	4	3	4	3	4	3.6	1	2	2	3	2	2	2.2
2	3	4	3	4	3	3.4	2	3	3	2	3	3	2.8
3	4	4	4	3	3	3.6	3	3	4	3	4	3	3.4
4	3	3	3	4	4	3.4	4	4	4	4	4	3	3.8
5	3	4	4	3	3	3.4	5	4	5	4	4	4	4.2
6	4	4	3	3	4	3.6	6	5	4	5	4	5	4.6
SD	.55	.52	.55	.52	.55		*SD*	1.05	1.03	1.05	.84	1.03	
Team *M*						3.5	Team *M*						3.5
Team *SD*						.54	Team *SD*						1.00

Figure 2

Illustration of Network Density

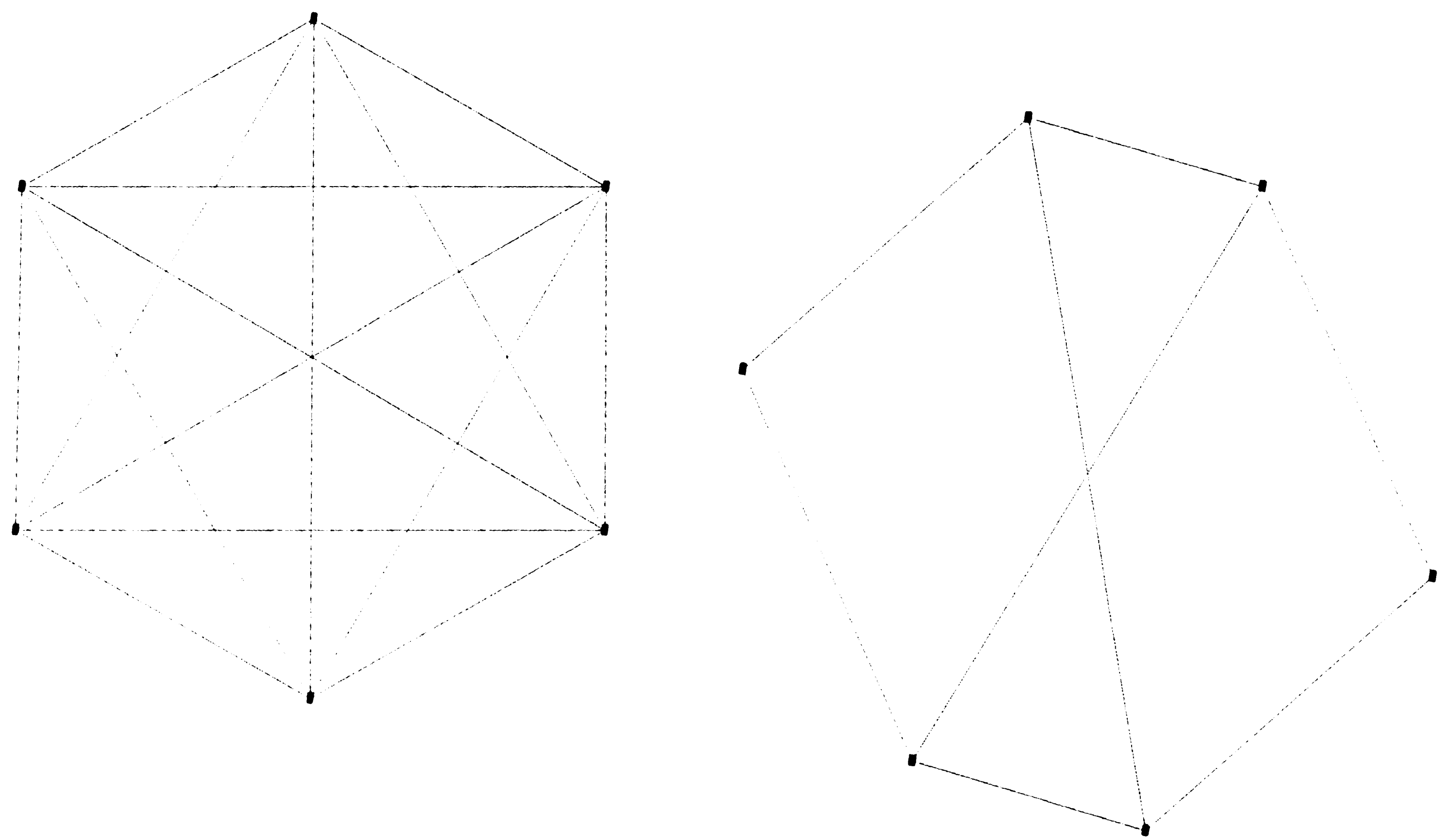
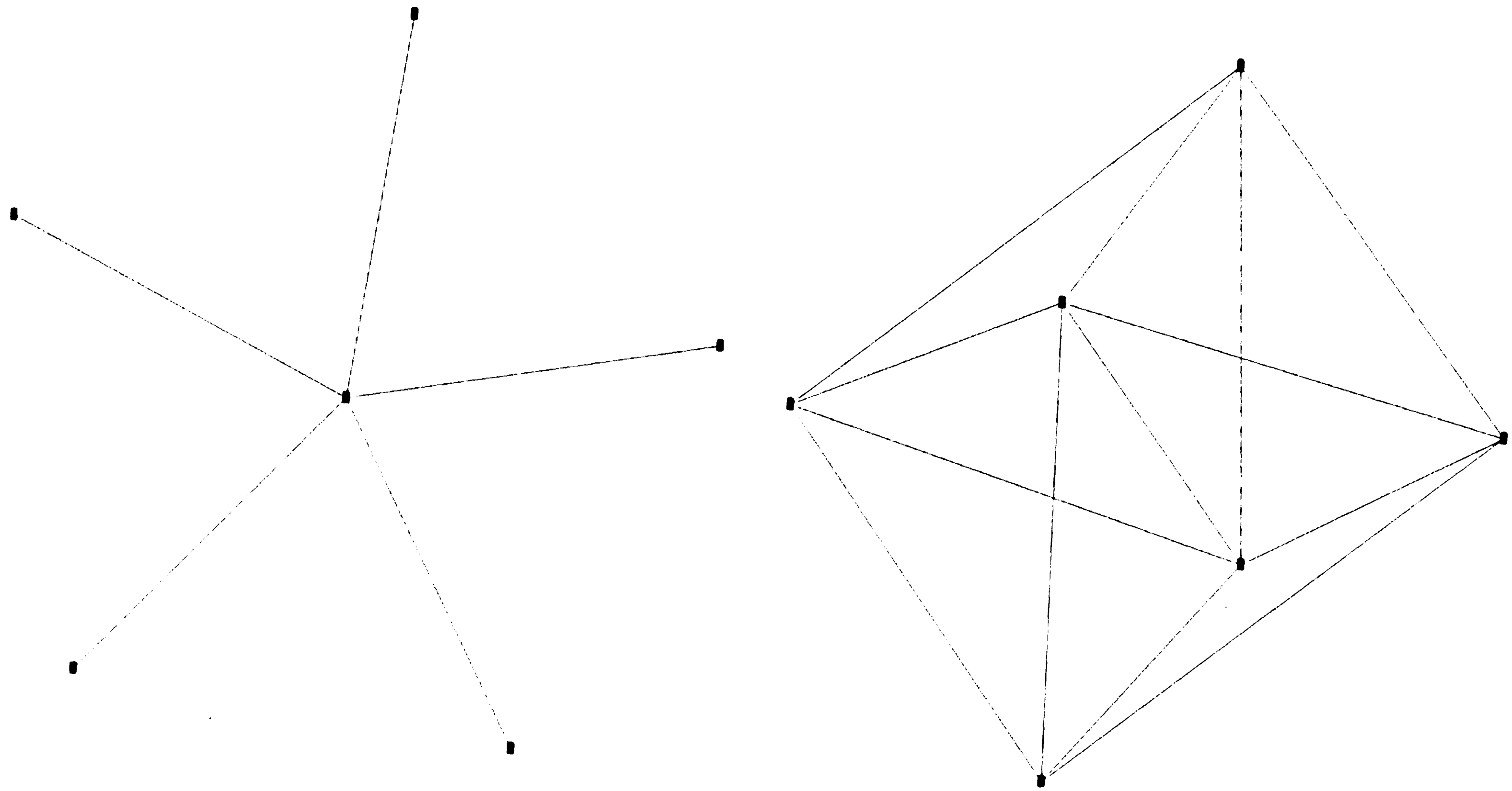


Figure 3

Illustration of Network Centralization



REFERENCES

Arthur, W., Bell, S. T., & Edwards, B. D. (2007). A longitudinal examination of the comparative criterion-related validity of additive and referent-shift consensus operationalizations of team efficacy. *Organizational Research Methods, 10*, 35-58.

Baerveldt, C., & Snijders, T. A. B. (1994). Influences on and from the segmentation of networks: Hypotheses and tests. *Social Networks, 16*, 213-232.

Baldwin, T. T., Bedell, M. D., & Johnson, J. L. (1997). The social fabric of a team-based M.B.A. program: Network effects on student satisfaction and performance. *Academy of Management Journal, 40*, 1369-1397.

Balkundi, P., & Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *Academy of Management Journal, 49*, 49-68.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*, 191-215.

Bandura, A. (1993). Perceived self-efficacy in cognitive-development and functioning. *Educational Psychologist, 28*, 117-148.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: Freeman.

Bandura, A. (2006). Guide for creating self-efficacy scales. In F. Pajares & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307-337). Greenwich, CT: Information Age Publishing.

Bavelas, A. (1950). Communication patterns in task-oriented groups. *Journal of the Acoustical Society of America, 22*, 723-730.

Bliese, P. D., & Halverson, R. R. (1998). Group consensus and psychological well-being: A large field study. *Journal of Applied Social Psychology, 28*, 563-580.

Blumer, H. (1969). *Symbolic interactionism: Perspective and method.* Englewood Cliffs, NJ: Prentice-Hall.

Boardley, I. D., Kavussanu, M., & Ring, C. (2008). Athletes' perceptions of coaching effectiveness and athlete-related outcomes in rugby union: An investigation based on the coaching efficacy model. *The Sport Psychologist, 22*, 269-287.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *Ucinet for Windows: Software for social network analysis.* Harvard, MA: Analytic Technologies.

Borgatti, S. P., & Foster, P. C. (2003). The network paradigm in organizational research: A review and typology. *Journal of Management, 29*, 991-1013.

Brass, D. J. (1984). Being in the right place: A structural analysis of individual influence in an organization. *Administrative Science Quarterly, 29*, 518-539.

Brass, D. J., Butterfield, K. D., & Skaggs, B. C. (1998). Relationships and unethical behavior: A social network perspective. *Academy of Management Review, 23*, 14-31.

Brown, K. G., Kozlowski, S. W., & Hattrup, K. (1996, August). *Theory, issues, and recommendations in conceptualizing agreement as a construct in organizational research: The search for consensus regarding consensus.* Paper presented at the Academy of Management Annual Meeting, Cincinnati, Ohio.

Burkhardt, M. E. (1994). Social interaction effects following a technological change: A longitudinal investigation. *Academy of Management Journal, 37*, 869-898.

Burkhardt, M. E., & Brass, D. J. (1990). Changing patterns or patterns of change: The effect of a change in technology on social network structure and power. *Administrative Science Quarterly, 35*, 104-127.

Burleson, B. R., Kunkel, A. W., Samter, W., & Werking, K. J. (1996). Men's and women's evaluations of communication skills in personal relationships: When sex differences make a difference and when they don't. *Journal of Social and Personal Relationships, 13*, 201-224.

Burt, R. S. (1987). Social contagion and innovation: Cohesion vs. structural equivalence. *American Journal of Sociology, 92*, 1287-1335.

Campion, M. A., Medsker, J. G., & Higgs, A. C. (1993). Relations between work group characteristics and effectiveness: Implications for designing effective work groups. *Personnel Psychology, 46*, 823-850.

Carron, A. V., Brawley, L. R., & Widmeyer, W. N. (1998). The measurement of cohesiveness in sport groups. In J. L. Duda (Ed.), *Advances in sport and exercise psychology measurement* (pp. 213-226). Morgantown, WV: Fitness Information Technology.

Carron, A. V., Widmeyer, W. N., & Brawley, L. R. (1985). The development of an instrument to assess cohesion in sport teams: The Group Environment Questionnaire. *Journal of Sport Psychology, 7*, 244-266.

Chan, D. (1998). Functional relationships among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology, 83*, 234-246.

Chase, M. A., Feltz, D. L., & Lirgg, C. D. (2003). Sources of collective efficacy and individual efficacy of collegiate athletes. *International Journal of Sport and Exercise Psychology, 1,* 180-191.

Chen, G., & Bliese, P. D. (2002). The role of different levels of leadership in predicting self- and collective efficacy: Evidence for discontinuity. *Journal of Applied Psychology, 87*, 549-556.

Chen, G., Webber, S. S., Bliese, P. D., Mathieu, J. E., Payne, S. C., Born, D. H., & Zaccaro, S. J. (2002). Simultaneous examination of the antecedents and consequences of efficacy beliefs at multiple levels of analysis. *Human Performance, 15*, 381-409.

Chow, G. M., Dithurbide, L., & Feltz, D. L. (2009, June). *Going beyond level of analysis: Examining dispersion as a team-level construct.* Paper presented at the North American Society for the Psychology of Sport and Physical Activity Annual Conference, Austin, Texas.

Chow, G. M., & Feltz, D. L. (2007). Exploring new directions in collective efficacy and sport. In M. R. Beauchamp & M. Eys (Eds.), *Group Dynamics Advances in Sport and Exercise Psychology: Contemporary Themes*. UK: Routledge.

Chow, G. M., & Feltz, D. L. (2008). Exploring the relationships between collective efficacy, perceptions of success, and team attributions. *Journal of Sports Sciences, 26*, 1179-1189.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95-S120.

Cummings, J. N., & Cross, R. (2003). Structural properties of work groups and their consequences for performance. *Social Networks, 25*, 197-281.

Dean, J. W., & Brass, D. J. (1985). Social interaction and the perception of job characteristics in an organization. *Human Relations, 38*, 571-582.

DeRue, D. S., Hollenbeck, J. R., Ilgen, D. R., & Feltz, D. L. (in press). Efficacy dispersion in teams: Moving beyond agreement and aggregation. *Personnel Psychology*.

Earley, P. C., & Mosakowski, E. (2000). Creating hybrid team cultures: An empirical test of transitional team functioning. *Academy of Management Journal, 43*, 26-49.

Feltz, D. L., & Lirgg, C. D. (1998). Perceived team and player efficacy in hockey. *Journal of Applied Psychology, 83,* 557-564.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7,* 117-140.

Festinger, L., Schachter, S., & Black, K. W. (1950). *Social Pressures in Informal Groups: A Study of Human Factors in Housing.* New York: Harper.

Frank, K. A. (1995). Identifying cohesive subgroups. *Social Networks, 17*, 27-56.

Frank, K. A. (1996). Mapping interactions within and between cohesive subgroups. *Social Networks, 18*, 93-119.

Frank, K. A., Muller, C., Schiller, K. S., Riegle-Crumb, C., Mueller, A. S., Crosnoe, R., & Pearson, J. (2008). The social dynamics of mathematics course-taking in high school. *American Journal of Sociology, 113*, 1645-1696.

Frank, K. A., & Yasumoto, J. Y. (1998). Linking action to social structure within a system: Social capital within and between subgroups. *American Journal of Sociology, 104*, 642-686.

Freeman, L. (1979). Centrality in social networks: Conceptual clarification. *Social Networks, 1*, 215-239.

Freeman, L. C. (1984). The impact of computer based communication on the social structure of an emerging scientific specialty. *Social Networks, 6*, 201-221

Friedkin, N. E. (1981). The development of structure in random networks: An analysis of the effects of increasing network density on five measures of structure. *Social Networks, 3*, 41-52.

Friedkin, N. E. (1984). Structural cohesion and equivalence explanations of social homogeneity. *Sociological Methods & Research, 12*, 235-261.

Friedkin, N. E. (1993). Structural bases of interpersonal influence in groups: A longitudinal case study. *American Sociological Review, 58*, 861-872.

Friedkin, N. E. (2001). Norm formation in social influence networks. *Social networks, 23*, 167-189.

Friedkin, N. E., & Cook, K. S. (1990). Peer group influence. *Sociological Methods & Research, 19*, 122-143.

Gibson, C. B. (1999). Do they do what they believe they can? Group efficacy and group effectiveness across tasks and cultures. *Academy of Management Journal, 42*, 138-152.

Gibson, C. B., Randel, A., & Earley, C. (2000). Understanding group efficacy: An empirical test of multiple assessment methods. *Group & Organization Management, 25*, 67-97.

Gibson, C. B., & Vermeulen, F. (2003). A healthy divide: Subgroups as a stimulus for team learning behavior. *Administrative Science Quarterly, 48*, 202-239.

Gist, M. E. (1987). Self-efficacy: Implications for organizational behavior and human resource management. *Academy of Management Review, 12*, 472-485.

Gonzalez-Roma, V., Peiro, J. M., & Tordera, N. (2002). An examination of the antecedents and moderator influences of climate strength. *Journal of Applied Psychology, 87*, 465-473.

Greenlees, I. A., Nunn, R. L., Graydon, J. K., & Maynard, I. W. (1999). The relationship between collective efficacy and precompetitive affect in rugby players: Testing Bandura's model of collective efficacy. *Perceptual and Motor Skills, 89,* 431-440.

Gully, S. M., Incalcaterra, K. A., Joshi, A., & Beaubien, J. M. (2002). A meta-analysis of team-efficacy, potency, and performance: Interdependence and level of analysis as moderators of observed relationships. *Journal of Applied Psychology, 87*, 819-832.

Hodges, L., & Carron, A. (1992). Collective efficacy and group performance. *International Journal of Sport Psychology, 23,* 48-59.

Ibarra, H. (1993). Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. *Academy of Management Journal, 36*, 471-501.

Ibarra, H., & Andrews, S. B. (1993). Power, social influence, and sense making: Effects of network centrality and proximity on employee perceptions. *Administrative Science Quarterly, 38*, 277-303.

Jackson, S. (1992). Team composition in organizations. In S. Worchel, W. Wood, & J. Simpson (Eds.), *Group Process and Productivity*. London: Sage.

Jackson, S., May, K. E., & Whitney, K. (1995). Understanding the diversity of dynamics in decision making teams. In R. A. Guzzo, E. Salas, & Associates (Eds.), *Team Effectiveness and Decision Making in Organizations*. San Francisco: Jossey-Bass.

James, L. R., Demaree, R. G., & Wolf, G. (1984). Estimating within-group rater reliability with and without response bias. *Journal of Applied Psychology, 69,* 85-98.

Jung, D. I., & Sosik, J. J. (2003). Group potency and collective efficacy: Examining their predictive validity, level of analysis, and effects of performance feedback on future group performance. *Group & Organization Management, 28*, 366-391.

Kilduff, M. (1990). The interpersonal structure of decision making: A social comparison approach to organizational choice. *Organizational Behavior and Human Decision Processes, 47*, 1-19.

Klein, K. J., Conn, A. B., Smith, D. B., & Sorra, J. S. (2001). Is everyone in agreement? An exploration of within-group agreement in employee perceptions of work environment. *Journal of Applied Psychology, 86*, 3-16.

Kozlowski, S. W. J., Gully, S. M., Nason, E. R., & Smith, E. M. (1999). Developing adaptive teams: A theory of compilation and performance across levels and time. In D. R. Ilgen, & E. D. Pulakos (Eds.), *The Changing Nature of Performance: Implications for Staffing, Motivation, and Development*, 240-292. San Francisco: Jossey-Bass Publishers.

Kozub, S. A., & McDonnell, J. F. (2000). Exploring the relationship between cohesion and collective efficacy in rugby teams. *Journal of Sport Behavior, 23,* 120-129.

Krackhardt, D. (1999). The ties that torture: Simmelian tie analysis in organizations. In S. B. Bacharach, S. B. Andrews, & D. Knoke (Eds.), *Research in the sociology of organizations,* vol. 16, 183-210. Stamford, CT: JAI Press.

Krackhardt, D., & Stern, R. N. (1988). Informal networks and organizational crisis: An experimental simulation. *Social Psychology Quarterly, 51*, 123-140.

Lau, D. C., & Murnighan, J. K. (1998). Demographic diversity and faultlines: The compositional dynamics of organizational groups. *Academy of Management Review, 23*, 325-340.

Lazer, D. M. (2001). The co-evolution of individual and network. *Journal of Mathematical Sociology, 25*, 69-108.

Leavitt, H. J. (1951). Some effects of certain communication patterns on group performance. *Journal of Abnormal and Social Psychology, 46*, 38-50.

Lichacz, F. M., & Partington, J. T. (1996). Collective efficacy and true performance. *International Journal of Sport Psychology, 27,* 146-158.

Linacre, J. M. (2002). Optimizing rating scale category effectiveness. *Journal of Applied Measurement, 3*, 85-106.

Lincoln, J. R., & Miller, J. (1979). Work and friendship ties in organizations: A comparative analysis of relational networks. *Administrative Science Quarterly, 24*, 181-199.

Lindell, M. K., & Brandt, C. J. (1997). Measuring interrater agreement for ratings of a single target. *Applied Psychological Measurement, 21*, 271-278.

Lindell, M. K., & Brandt, C. J. (2000). Climate quality and climate consensus as mediators of the relationship between organizational antecedents and outcomes. *Journal of Applied Psychology, 85*, 331-348.

Lindsley, D. H., Brass, D. J., & Thomas, J. B. (1995). Efficacy-performance spirals: A multilevel perspective. *Academy of Management Review, 20*, 645-678.

Lovelace, D., Shapiro, D. L., & Weingart, L. R. (2001). Maximizing cross-functional new product teams' innovativeness and constraint adherence: A conflict communications perspective. *Academy of Management Journal, 44*, 779-79.

Magyar, T. M., Feltz, D. L., & Simpson, I. P. (2004). Individual and crew level determinants of collective efficacy in rowing. *Journal of Sport & Exercise Psychology, 26,* 136-153.

Marsden, P. V., & Friedkin, N. E. (1993). Network studies of social influence. *Sociological Methods & Research, 22*, 127-151.

McGrath, J. E. (1984). *Groups, interaction, and performance.* Englewood Cliffs, NJ: Prentice-Hall.

Moritz, S. E., & Watson, C. B. (1998). Levels of analysis issues in group psychology: Using efficacy as an example of a multilevel model. *Group Dynamics: Theory, Research, and Practice, 2*, 285-298.

Morrison, E. W. (2002). Newcomers' relationships: The role of social network ties during socialization. *Academy of Management Journal, 45*, 1149-1160.

Mulvey, P. W., & Klein, H. J. (1998). The impact of perceived loafing and collective efficacy on group goal processes and group performance. *Organizational Behavior and Human Decision Processes, 74*, 62-87.

Mudrack, P. E. (1989). Defining group cohesiveness: A legacy of confusion? *Small Group Behavior, 20*, 37-49.

Myers, N. D., & Feltz, D. L. (2007). From self-efficacy to collective efficacy in sport: Transitional issues. In G. Tenenbaum, & R. C. Eklund (Eds.), *Handbook of sport psychology*, 3 ed. New York: Wiley.

Myers, N. D., Feltz, D. L., & Short, S. E. (2004). Collective efficacy and team performance: A longitudinal study of collegiate football teams. *Group Dynamics: Theory, Research, and Practice, 8*, 126-138.

Myers, N. D., Payment, C. A., & Feltz, D. L. (2004). Reciprocal relationships between collective efficacy and team performance in women's ice hockey. *Group Dynamics: Theory, Research, and Practice, 8*, 182-195.

Myers, N. D., Vargas-Tonsing, T. M., & Feltz, D. L. (2005). Coaching efficacy in intercollegiate coaches: Sources, coaching behavior, and team variables. *Psychology of Sport and Exercise, 6*, 129-143.

Parker, L. E. (1994). Perceived self-efficacy and collective-efficacy at the workplace. *Journal of Applied Social Psychology, 24*, 43-59.

Paskevich, D. M., Brawley, L. R., Dorsch, K. D., & Widmeyer, W. N. (1999). Relationship between collective efficacy and team cohesion: Conceptual and measurement issues. *Group Dynamics: Theory, Research, and Practice, 3*, 210-222.

Paxton, P., & Moody, J. (2003). Structure and sentiment: Explaining emotional attachment to group. *Social Psychology Quarterly, 66*, 34-47.

Pescosolido, A. T. (2003). Group efficacy ad group effectiveness: The effects of group efficacy over time on group performance and development. *Small Group Research, 34*, 20-42.

Peterson, E., Mitchell, T. R., Thompson, L., & Burr, R. (2000). Collective efficacy and aspects of shared mental models as predictors of performance over time in work groups. *Group Processes & Intergroup Relations, 3*, 296-316.

Portes, A., & Sensenbrenner, J. (1993). Embeddedness and immigration: Notes on the social determinants of economic action. *American Journal of Sociology, 98*, 1320-1350.

Prussia, G. E., & Kinicki, A. J. (1996). A motivational investigation of group effectiveness using social cognitive theory. *Journal of Applied Psychology, 81*, 187-198.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and*

data analysis methods. Newbury Park, CA: Sage.

Reagans, R., & Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science, 12*, 502-517.

Rentsch, J. R. (1990). Climate and culture: Interaction and qualitative differences in organizational meanings. *Journal of Applied Psychology, 75*, 668-681.

Roberson, Q. A., & Colquitt, J. A. (2005). Shared and configural justice: A social network model of justice in teams. *Academy of Management Journal, 30*, 595-607.

Scanlan, T. K., Carpenter, P. J., Schmidt, G. W., Simons, J. P., & Keeler, B. (1993). An introduction to the sport commitment model. *Journal of Sport & Exercise Psychology, 15*, 1-15.

Scanlan, T. K., Simons, J. P., Carpenter, P. J., Schmidt, G. W., & Keeler, B. (1993). The sport commitment model: Measurement and development for the youth sport domain. *Journal of Sport & Exercise Psychology, 15*, 16-38.

Schneider, B., & Reichers, A. E. (1983). On the etiology of climates. *Personnel Psychology, 36*, 19-39.

Schneider, B., Salvaggio, A. N., & Subirats, M. (2002). Climate strength: A new direction for climate research. *Journal of Applied Psychology, 87*, 220-229.

Scott, J. (2000). *Social network analysis: A handbook* (2^{nd} ed.). Thousands Oaks, CA: Sage.

Shah, P. P. (2000). Network destruction: The structural implications of downsizing. *Academy of Management Journal, 43*, 101-112.

Shaw, M. (1964). Communication networks. In L. Berkowitz (Ed.), *Advances in experimental psychology* (pp. 111-147). New York: Academic Press.

Shaw, M. E. (1954). Some effects of unequal distribution of information upon group performance in various communication nets. *Journal of Abnormal and Social Psychology, 49*, 547-553.

Silverman, D. (1971). *The theory of organizations: A sociological framework.* New York: Basic Books.

Smith, P. (1973). *Groups within organizations: Applications of social psychology.* New York: Harper and Row.

Sparrowe, R. T., Liden, R. C., Wayne, S. J., & Kraimer, M. L. (2001). Social networks and the performance of individuals and groups. *Academy of Management Journal, 44*, 316-325.

Spink, K. S. (1990). Group cohesion and collective efficacy of volleyball teams. *Journal of Sport & Exercise Psychology, 12,* 301-311.

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), *The Social Psychology of Intergroup Relations*. Monterey, CA: Brooks-Cole.

Totterdell, P., Wall, T., Holman, D., Diamond, H., & Epitropaki, O. (2004). Affect networks: A structural analysis of the relationship between work ties and job-related affect. *Journal of Applied Psychology, 89*, 854-867.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, Cambridge University Press.

Watson, C. B., Chemers, M. M., & Preiser, N. (2001). Collective efficacy: A multilevel analysis. *Personality and Social Psychology Bulletin, 27,* 1056-1068.

Wilson, P. M., Rodgers, W. M., Carpenter, P. J., Hall, C., Hardy, J., & Fraser, S. N. (2004). The relationship between commitment and exercise behavior. *Psychology of Sport & Exercise, 5*, 405-421.

Zaccaro, S. J., Blair, V., Peterson, C., & Zazanis, M. (1995). Collective efficacy. In J. E. Maddux (Ed.), *Self-efficacy, adaptation and adjustment: Theory, research and application* (pp. 308-330). New York: Plenum.

Zhu, W., & Kang, S. J. (1998). Cross-cultural stability of the optimal categorization of a self-efficacy scale: A Rasch analysis. *Measurement of Physical Education and Exercise Science, 2*, 225-241.

Zhu, W., Updyke, W. F., & Lewandowski, C. (1997). Post-hoc Rasch analysis of optimal categorization of ordered-response scale. *Journal of Outcome Measurement, 1*, 286-304.

Zohar, D., & Tenne-Gazit, O. (2008). Transformational leadership and group interaction as climate antecedents: A social network analysis. *Journal of Applied Psychology, 93*, 744-757.