Identifying the Strategic Core of Interactive Teams

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Identifying the Strategic Core of Interactive Teams

A Thesis

Presented in

Partial Fulfillment of the

Requirements for the Degree of

Master of Arts

By

Morgan Elizabeth Gleason

June 1, 2021

The Department of Psychology

College of Science and Health

DePaul University

Chicago, Illinois
Thesis Committee

Goran Kuljanin, PhD, Chair

Alice Stuhlmacher, PhD
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Biography

The author was born in Valhalla, NY on May 13, 1986. She graduated from Monroe-Woodbury High School in Central Valley, NY in 2004. She received her bachelor’s degree from Johnson & Wales University in 2008 and her Master of Arts degree in Psychology from the State University of New York at New Paltz in 2014.
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Abstract

This paper examines how the strategic core of interactive teams can be identified and examined using interactive process data. The IOP literature suggests that certain key members contribute more to team outcomes than others (Barker, 1993; Sparrowe et al., 2001). Key members of a team comprise a “strategic core,” encountering more job-relevant tasks and problems, thereby contributing more to team performance (Barker, 1993). This research used manually coded passing data from 1,309 games of the 2016-2017 National Basketball Association (NBA) season and player statistics reported by the NBA to examine the structure of the strategic core of basketball teams based on social network metrics, player positions and player and team performance statistics (NBA Media Ventures, LLC, 2020). Social Network Analysis (SNA) metrics and Profile Analysis were used to examine whether (and how) the core structure varied among performance episodes for the same team and between teams across the season. Lastly, this research examined how the qualities of core players were impacted by team strategy (broader team interactions).

Keywords: Social network analysis, profile analysis, team dynamics, team effectiveness, team composition, team performance, role theory
Introduction

Effective collaboration, like that of players on a successful sports team, is the goal of countless managers in today’s organizations. The question remains: how can the unique talents of each member best be harnessed to elicit effective team performance? Team collaboration is a vital area of research in the field of industrial-organizational psychology (IOP) (Cohen et al., 1996; Devine et al., 1999; Eys, Bruner & Martin, 2019; Lawler et al., 1992; Morgeson et al., 2005). A key aspect of the selection process involves identifying whether potential employees have the knowledge, skills, and abilities for effective teamwork (Larson & LaFasto, 1989).

Another important consideration is each member's role within the context of the team setting (Sundstrom, 1990). In fact, teams have been defined in the extant literature as a system of roles (Bales, 1950). A role is a collection of related goal-directed behaviors characteristic of a person within a specific situation (Stewart et al., 1999; 2005). Understanding, standardizing, and properly staffing each role is the blueprint for forming an effective team (Ancona & Caldwell, 1988; Belbin, 1993). These steps are vital to fostering coordination among team members, avoiding process loss (Hollenbeck et al., 2002; Humphrey et al., 2009; Steiner, 1972), and properly allocating resources among team members (Kozlowski & Klein, 2000). The current research was aimed at taking unique team roles into consideration in measuring both individual-level and team-level processes and outcomes. This goal for this research was to identify and describe the core roles of teams and explore whether they varied over time.

Literature on teams asserts that roles are crucial to understanding organizational processes on a broader level (Katz & Kahn, 1978). This is because roles provide the additional context within which to conceptualize the individual at differing theoretical levels (Katz & Kahn, 1978). Roles inform our expectations for the behavior of the individual and point to the
functional requirements of the broader team or organization (Katz & Kahn, 1978). In other words, roles define the processes that a team undertakes to accomplish goals (Katz & Kahn, 1978). The Input-Process-Output (IPO) Model (Hackman, 1987; McGrath, 1964) considers the inputs, processes, and outputs of teams (Ilgen, et al., 2005; Marks, Mathieu & Zaccaro, 2001; McGrath, 1964). Inputs are antecedents that impact team interactions such as individual characteristics or abilities of team members or specific features of the task or work context (Mathieu et al., 2008). Processes generally refer to the interactions that take place between team members motivated by individual and team goal attainment. Outcomes are results or performance criteria which are typically measured by assessing strategic end states (e.g., goal completion, customer satisfaction, reported team satisfaction).

Researchers have posited that broader-level factors (contextual variables) can sometimes impact lower-level factors (team inputs) asserting that team processes are bidirectional (Cohen & Bailey, 1997). Developmental models of team performance incorporate temporal concerns by focusing on how team characteristics change as teams gain experience (Kozlowski, Gully, Nason & Smith, 1999), while episodic approaches illustrate why certain tasks must be executed at specific times depending on recurring task demands within a cyclical framework (Marks et al., 2001). Seminal work by Marks, Mathieu, and Zaccaro (2001) viewed teams through this episodic lens, identifying that emergent states such as affect, behaviors, and cognitions of team members often mediate team outcomes. Ilgen et al. (2005) integrated this thinking in the development of what is known as the Input-Mediator-Outcome (IMO) model as an extension of the original IPO framework. These researchers, recognizing the cyclical nature of teams, further expanded this work to coin the Input-Mediator-Outcome-Input (IMOI) model (Ilgen et al., 2005). While the development of theory surrounding teams has been robust and thoughtful, the
literature has retained a continued focus on the effects of team inputs on team outcomes, while missing an empirical understanding of how team member interactions and resulting team processes impact team outcomes (Humphrey & Aime, 2014; Mathieu et al., 2008). The incorporation of theories related to differentiated roles within teams and tracking team member interactions could aid in advancing our understanding of teams.

While the teams literature has a rich and complex history, little is known about how dynamic team interactions inform outcomes (Mathieu et al., 2008). While many researchers theorize about team processes, few track the unfolding set of team member interactions that lead to team processes (Illgen et al., 2005; Mathieu et al., 2008; Marks et al., 2001). The majority of team research utilizes self-report measures to infer team processes based on emergent states (e.g., team mental models, team efficacy, team satisfaction). Due to the need for standardization and other constraints, these studies typically involve ad hoc teams in lab settings that treat team roles as uniform (Beersma et al., 2003; Breugst et al., 2012; Marks et al., 2000; Mathieu et al., 2000; Mathieu et al., 2005; Mell, Van Knippenberg & Van Ginkel, 2012; Pearsall, Ellis & Bell, 2010; Van Kleef et al., 2009; Villado & Arthur, 2013; Wagner et al., 2012). Differentiated roles are seldom studied with the exception of the development of team typologies (Belbin, 1993; Mumford, Campion & Morgeson, 2006; Mumford et al., 2008). Moreover, the aggregation of traits and abilities across individuals in the teams literature (Harrison & Klein, 2007; Humphrey, Morgeson, & Manor, 2009; LePine, Hollenbeck, Ilgen & Hedlund, 1997) assumes that teams are a collection of undifferentiated roles, although in reality this is rarely the case. Further study was needed to unravel the differential impact each team member has on team outcomes and how this changes and unfolds over time both within and across roles.
This research focused on how team interactions impact team outcomes by utilizing general social network analysis (SNA) and profile analysis (Desjardins & Bulut, 2017; Harris, 2013; Kilduff & Brass, 2010). This approach quantified observable team interactions that contributed to results. By incorporating team roles and using observed team interactions data, the current study aimed to further understand team functioning.

**Team Effectiveness**

The study of teams, and team performance in particular, is a popular topic in IOP (Cascio & Aguinis, 2008). Recent literature on team performance in top IOP journals is concerned mainly with how team inputs impact the mechanisms or processes that contribute to team outcomes (Carter, Carter & DeChurch, 2018; Li, Liao, Tangirala & Firth, 2017; Lvina, Johns & Vandenbergh, 2018; Nederveen Pieterse, Van Knippenberg & Van Dierendonck, 2013; Schippers, 2014; Troth, Jordan, Lawrence & Tse, 2012). The current literature adds much to our understanding of how inputs (e.g., dispositional factors and team member skills/abilities) influence team processes or “emergent states” (Humphrey & Aime, 2014). A focus on the composition of individual-level cognitive variables such as emotional skill (Troth, Jordan, Lawrence & Tse, 2012), goal-orientation (Nederveen Pieterse, Van Knippenberg & Van Dierendonck, 2013), and personality variables (Schippers, 2014) is typical of the team performance literature. While team processes and mediating variables appear to be of great interest in the field, often these constructs are aggregated to the team level, in lieu of attempts to capture “patterns” of behavioral interactions between team members (Crawford & LePine, 2013).

An example that helps illustrate a common methodology in the study of team performance examined trait activation in teams of university students working on a course
project (Schippers, 2014). Schippers (2014) posited that agreeableness and conscientiousness would moderate the relationship between social loafing and team performance. For teams scoring high on social loafing, differential performance outcomes were predicted based on team-level agreeableness and conscientiousness. Schippers (2014) hypothesized that high levels of agreeableness and conscientiousness would provide a buffering effect, facilitating enhanced performance. On the other hand, for teams that scored low on social loafing tendencies, conscientiousness was found to have a weaker impact than agreeableness on performance. This provides an interesting theoretical perspective on how team members' interactions influence team outcomes. In this particular study, each construct was measured using self-report questionnaires, with the exception of performance (which was measured using students' course grades) (Schippers, 2014). The above-mentioned study is typical in that cognitive inputs (e.g., social loafing, agreeableness, conscientiousness) are considered and interactions between team members are not measured behaviorally. This methodology obscures the unique contribution each team member makes to team outcomes, assuming that all team members contribute equally.

Other inputs of interest are mechanisms or processes that impact team outcomes (Crawford & LePine, 2013; Ilgen, Hollenbeck, Johnson & Jundt, 2005; Mathieu et al., 2008). For example, team innovation (Li, Liao, Tangirala & Firth, 2017), calibration (Carter, Carter & DeChurch, 2008), mental models (Lim & Klein, 2006; Mathieu et al., 2005) and cohesion are of interest to researchers (Lvina, Johns & Vandenberghe, 2018). These cognitive constructs are measured primarily with self-report reflections on team experiences (Carter, Carter & DeChurch, 2008; Lim & Klein, 2006; Lvina, Johns & Vandenberghe, 2018). One noteworthy exception is the study conducted by Mathieu et al. (2005) in which participants were trained to complete a computerized flight mission in teams of three. Although participant’s mental models were
assessed using a self-report scale, team processes were rated by subject matter experts who viewed the tape-recorded computerized flight simulations and reported observations about participants' relevant behaviors (Mathieu et al., 2005). While this study is particularly impressive in its theoretical depth and comprehensive design, it too employs self-report measures of cognitive constructs as the main thrust of its design. Outcome measures vary depending on the nature of the study, but typically rely on project grades in the case of laboratory studies (Gevers & Peeters, 2009; Hu & Liden, 2015; Johnson et al., 2015; Lvina, Johns & Vandenberghe, 2018; Mathieu et al., 2007; Mathieu & Shultz, 2006; Mehta et al., 2006; Nederneen Pieterse, Van Knippenberg & Van Dierendonck, 2013; Schippers, 2014; Sherf et al., 2018; Troth et al., 2012;) and customer satisfaction and manager ratings in field studies (Chun, Cho & Sosik, 2016; Chung & Jackson, 2013; Elsass, 2001; Lim & Klein, 2006; Mohammed & Nadkarni, 2001; Mohammed & Nadkarni, 2014; Schaubroeck et al., 2011; Stewart & Barrick, 2000; Stewart et al., 2012). The addition of process data that captures team interactions and behavioral measures that tap performance can strengthen our understanding of the ways in which different team members influence individual and team outcomes.

**Team Role Theory**

Roles provide clarity with respect to the purpose of each team member’s task, duties, and responsibilities (Humphrey et al., 2009; Mumford et al., 2008). Roles provide a script for the collection of expected team members behaviors that inform the broader pattern of team interaction expected from the team as a whole (Kozlowski & Klein, 2000). Roles are the mechanism that link individual team member traits and abilities to team outcomes (Stewart et al., 2005). For example, consideration of who should fill each role on a team is essential to the effective combination of knowledge, skills, and abilities of each member which, if poorly
assigned, leads to conflict or inefficient interactions (Mumford, Van Iddekinge, Morgeson & Campion, 2008; Steiner, 1972). Roles are considered to be the building blocks of teams because the amalgamation of individual-level roles informs the functional performance of the team (Stewart et al., 2005).

Roles are an essential consideration in conceptualizing how teams interact and perform (Stewart et al., 2005). Essentially, team performance is the result of the execution of interconnected roles (Humphrey et al., 2009). It is also important to note that the literature asserts that in applied settings some roles are more important to team outcomes than others (Belbin, 1993; Lawrence & Lorsch, 1969; Mumford, Campion & Morgeson, 2006; Mumford et al., 2008). This argument seems plausible when you consider how teams relate to the broader organizational level. According to the Pareto principle, the top twenty percent of the workforce is responsible for eighty percent of an organization’s output (Sanders, 1987). In other words, the top performers in any organization contribute more to the organization’s success than mediocre and low performers combined. The theory underlying competitive advantage assumes that certain teams are more closely linked to organizational strategy, and, thus, more important to key organizational functions (e.g., marketing vs research and development) (Humphrey et al., 2009). This leads to the question: is each member's contribution to team outcomes identical? It is unlikely that in team contexts each role has the same impact on performance. Indeed, the purpose of creating a team is often the need for individuals to take on specific tasks based on ability (Humphrey et al., 2009). While the assumption of undifferentiated team roles allows for simplified laboratory experiments, it appears inappropriate to the study of applied teams. In the same way that team performance is differentially related to organizational outcomes, key or
“core” roles within the team structure are those that have a comparatively larger impact on performance (Humphrey et al., 2009).

Modern teams are more dynamic and interconnected than ever, making it difficult to identify individual contributions to team outcomes. Researchers in the field have identified the need for a framework to quantify individual contributions to team outcomes within complex, dynamic systems (Bell, 2007; Carter, Carter & DeChurch, 2018; Kozlowski & Chao, 2012). The need for additional empirical work related to role-based performance is also mentioned (Humphrey et al., 2009). Certain role-based theories, for instance, define core roles as those that have the largest impact on performance - allowing only for later identification of the strategic core once outcome variables have been captured (Humphrey et al., 2009). A shift towards understanding how team members interact within their roles to achieve team outcomes would be a useful addition to the literature. In addition to considering performance, specific features of roles that comprise a team’s core have been identified but would benefit from additional study related to identification of how roles differentially impact team performance (Humphrey et al., 2009).

The strategic core of a team can be identified by careful consideration of the flow of information between team members, relative exposure to tasks and problems, and measuring the ways in which interaction patterns unfold within a team (Humphrey et al., 2009). Core roles are those that are exposed to more problems that arise in the team context (Barker, 1993). In addition, involvement in more goal-relevant tasks makes a role more core than a role with fewer goal-relevant tasks (Moon et al., 2004). Another consideration involves the workflow of the team. The more dominant individuals are within the work process, or interconnected they are to others within the team, the more likely it is that their role is part of the strategic core of the team.
(Sparrowe et al., 2001). Arguably, part of the reason teams are treated as undifferentiated in the literature is because identifying the core of the team in this way is difficult because of the preplanning needed to experimentally assign team members to differentially important roles. Even upon gathering data on applied teams, the strategic core could be identified in myriad ways. An important question arises when different individuals can be assigned to the same role on a team, and, thus, change the “coreness” of a particular role (Sparrowe et al., 2001). Questions related to quantifying the impact of key team roles and capturing their relation to team performance necessitate the use of analytical methods that aid in capturing and visualizing the complex interactions between individuals in social systems. Social network analysis can illuminate how different team roles interact to carry out team processes, helping to identify which roles encounter more problems, are involved in more of the tasks within the team process, and contribute directly or indirectly to team outcomes. In the next section, I discuss social network analysis from a conceptual level and describe how it was used to identify the strategic core of teams.

**Social Network Analysis**

Social network analysis (SNA) is an analytical tool to evaluate connections between entities (e.g., team members) of interest (Borgatti & Halgin, 2011; Sparrowe et al., 2001). A social network is a collection of individual actors whose recorded relational interactions or “ties” are aggregated to form a visual web (Katz et al., 2004). Relational ties can be defined across a variety of dimensions including things such as the exchange of money or information, conversations between individuals, or physical closeness or reported familiarity (Katz et al., 2004). These ties form the visible output or the footprint of the network (Katz et al., 2004; Borgatti & Halgin, 2011). In visualizing data in this way, it becomes possible to deduce which
actors are central to the given network (e.g., have many connections with a number of other actors) or which dyads are interacting with the most frequency (e.g., reciprocity) (Katz, et al., 2004).

Social networks can be constructed in many ways (Borgatti & Halgin, 2011; Sparrowe et al., 2001). A social network can be derived by observing physical interactions between players on a sports team during a performance episode (e.g., counting the number of times the ball is passed between players in a particular game), or by asking employees to indicate which people within their organization they have contact with and how often (Katz et al., 2004). Once data such as these are collected, an algorithm can be used to create a visual representation of network features such as how densely (i.e., well-connected) or sparsely connected (i.e., isolated) each individual actor is within the specified network (Kilduff & Brass, 2010). Copious features of the network can also be determined using SNA. For instance, SNA can reveal the longest path in the network from one actor to another, reveal whether activity is dominated by one or two actors or evenly spread across them, and indicate which actors are the most vital to the flow of information (Kilduff & Brass, 2010). Each of these metrics provide insights into the processes formed via the interactions that take place between actors in the network. In the examples given, the definition of what constitutes a tie between actors varies conceptually (e.g., social interconnectedness vs. physical interconnectedness). Nevertheless, specific network metrics can be calculated in the same way in either scenario (e.g., based on the number of connections between individuals in relation to the total number possible).

The study of interactive teams necessitates an analytical approach that captures the observable interactions between teammates and informs how individual within-role performance impacts other players as well as team performance (Katz et al., 2004). One of the strengths of
this approach is that it measures teams and organizations plainly as a system of interconnected actors (Tichy, Tushman & Fombrun, 1979). In this way, SNA captures the dynamic complexity of relationships between individuals allowing for analysis at the individual (i.e., “node”) and group (i.e., “network”) level based on actual interactions and not proxies. This is useful because it bypasses the reliance on self-report measures and individual attributes in predicting team outcomes (Mathieu et al., 2008).

There are two levels of analysis that serve as a guide in conceptualizing SNA metric calculations: the individual-level and the network-level (Kilduff & Brass, 2010). The individual-level provides information about how each actor’s interactions compare with other nodes in the network writ large (Kilduff & Brass, 2010). One of the individual-level calculations is centrality. A central node within a network is an actor that has a relatively high frequency of incoming and outgoing information/exchanges (Kilduff & Brass, 2010). For instance, if actor A in a network is given information only from actor B, but actor B is fed information from C, D, and E, then actor B has higher in-degree centrality than actor A. This is due the number of connections to B from others compared to actor A within the network. Centrality can be calculated using different methods (Kilduff & Brass, 2010). If an actor has high eigenvector centrality it tells us that they are influential within the network compared to others because the score indicates they are closely tied with a large proportion of other actors who are well-connected in the network (Kilduff & Brass, 2010). (See Table 1).

Table 1

*Player-level Metrics Derived Using Social Network Analysis*

<table>
<thead>
<tr>
<th>Player-level Metric</th>
<th>Conceptual Definition*</th>
</tr>
</thead>
</table>
Closeness Centrality  The extent to which an actor is close to others in terms of number of connections

Betweenness Centrality  The degree to which a node falls between two other nodes on the shortest path between those two actors

In-degree Centrality  The number of directional links to that actor from other actors

Out-degree Centrality  The number of directional links that actor to other actors

*(Kilduff & Brass, 2010)*

Network-level metrics are features related to interaction patterns that have emerged across the network (See Table 2). One network-level metric is closeness centralization (Katz et al., 2004; Kilduff & Brass, 2010). While centrality scores reveal information at the node-level, centralization reveals how centralized the network is overall. Closeness centralization indicates how easily one actor can reach all others in the network (Kilduff & Brass, 2010). According to Kilduff and Brass (2010) closeness centralization is helpful because it provides information on how easily information or resources are communicated through the network in the form of workflow. A second network-level metric is density (Kilduff & Brass, 2010). Density provides a measure of the interconnectedness of nodes in a network (Kilduff & Brass, 2010). Density is a ratio of the proportion of ties in the network in question over the number of potential ties (Kilduff & Brass, 2010). Sometimes used as a measure of cohesion, density is a measure of how dense (e.g. if density is high) or sparse (e.g., if density is low) the links in the network are on average (Kilduff & Brass, 2010). These measures quantify how interconnected a network is compared with the total possible number of connections between actors (Kilduff & Brass, 2010). A metric related to the quality of ties is reciprocity (Kilduff & Brass, 2010; Lusher et al., 2014). Reciprocity provides an indication of whether ties in the network tend to be unidirectional or mutual between pairs of actors (Kilduff & Brass, 2010) Each measure of centrality gives us
specific information about the ways in which the actor is connected to others (e.g., closeness, directionality, number of indirect connections, etc.) (Kilduff & Brass, 2010). Each of these network-level metrics represents patterns of interactions in slightly different ways and allows for a nuanced examination of how the structure of interactions is unfolding in the group (See Table 2). It is important to note, however, that not all patterns are meaningful. SNA researchers warn that patterns (e.g., the formation of triads) can emerge even in randomly generated networks (Lusher et al., 2014). For this reason, additional analytical methods are needed to reveal the importance of certain patterns of relationships in a network.

Table 2

*Network Metrics Derived Using Social Network Analysis*

<table>
<thead>
<tr>
<th>Network-level Metric</th>
<th>Conceptual Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Density</strong></td>
<td>The proportion of connections in the network divided by all possible connections that could exist (Kilduff &amp; Brass, 2010)</td>
</tr>
<tr>
<td><strong>Centralization</strong></td>
<td>The degree to which a Network’s nodes have connections to other Nodes in the network (Kilduff &amp; Brass, 2010)</td>
</tr>
<tr>
<td><strong>Transitivity</strong></td>
<td>The extent to which there are closed triadic relations with others (Lusher, Robins, &amp; Kremer, 2010)</td>
</tr>
<tr>
<td><strong>Diameter</strong></td>
<td>Length of the longest path between nodes in a network (Kilduff &amp; Brass, 2010)</td>
</tr>
<tr>
<td><strong>Distance</strong></td>
<td>Minimum number of paths to connect nodes in a network (Kilduff &amp; Brass, 2010)</td>
</tr>
<tr>
<td><strong>Reciprocity (dyadic)</strong></td>
<td>The extent to which network ties are mutual</td>
</tr>
</tbody>
</table>
Rationale for the Proposed Research

The aim of this study was to understand how team members structure themselves to maximize team success with a focus on understanding the strategic cores of teams. NBA teams provided a useful sample due to the nature of observable interaction inherent in televised sports, and the availability of archival game footage and relevant performance statistics. Tables 1 and 2 present 10 node-level and network-level SNA metrics to examine the interactional and network structures of highly interactive teams. Initially, data were aggregated across games to identify and define the construct of the strategic core itself. By regressing individual performance data on composite player-level centrality metrics, I identified whether coreness of players predicted PIE scores (this was calculated both irrespective of team membership across the season, and within teams across the season). Furthermore, I examined what types of players (e.g., based on formal team roles) typically make up the “strategic core” across the 30 NBA teams, and whether the strategic core changes across the NBA season within teams. Lastly, I explored how team-level interaction patterns enhance and/or inhibit the success of players that display the node-level features of core players. This approach began with examining how centrality scores at the node-level were related to PIE scores across teams.

Research Questions

RQ I: How can we best define the strategic core of the teams in question?

RQ II: Is the strategic core consistent across teams?

RQ III: Does the strategic core of a team change over the season?

RQ IV: How does the overall team network affect the contributions of core players?
**RQ1: Structure of the core**

I examined the extent to which two perspectives (interaction data and outcome data) aligned with respect to forming the core of a team. The first research question dealt with identifying the strategic core of NBA basketball teams using both social network measures and behaviorally based performance measures. In organizations, there are key employees who encounter more of the problems associated with business operations and contribute more to performance relative to other employees (Barker, 1993).

**RQ2: Consistency of the core across teams**

Because various teams utilize different strategies to achieve performance, it is possible that the interaction patterns that predict success for core players on one team may not be good predictors of success for the core of a different team. In other words, it is likely that different interaction patterns contribute to successful outcomes for different teams, and less likely that node-level predictors of performance are consistent across teams. There are many ways to execute a particular role on the court, and different strategies are used in combination to achieve high performance. If certain node level metrics consistently predict player level success, other factors need to be considered. For instance, perhaps a particular court position (e.g., small forward, center) dominates the court across teams simply because players in these roles are more likely to obtain possession of the ball. By assessing which node-level metrics were predictive of individual player win share across teams, I examined how the interactive process on the court facilitated performance outcomes on the player level. Examining profile plots allowed for further analysis of how specific node-level metrics contributed to performance in different team contexts.
RQ3: Consistency of the core within teams across the season

Once the core of a team was identified on an aggregated level (over the course of all games played by each team), I examined the extent to which the qualities of the core changed over the course of the season. While regressing the node-level metrics aggregated across all games can assist in simplifying team interactions and help elucidate the strategic core, it also obscures how player interactions change over different performance episodes. An important consideration is how the same players interact and perform across different games. It was interesting to see how node-level metrics that were predictive of core player performance at the season-level were related to player level performance when we consider each game independently. I examined whether the same players comprise the core from one game to the next. In addition, I examined whether the node-level metrics that predict individual performance of core players are consistent from game to game. I was interested in understanding whether the same players comprise the core from game to game, or if the composition of the core changed across the season. I examined the same team across performance episodes to understand whether the strategic core of the team changed and how.

RQ4: How the team facilitates its core

In attempting to understand how the strategic core of the team changes from game to game, I also considered team context. I surmised that perhaps certain node-level metrics facilitated individual performance only when specific team-level interactions were present. For instance, perhaps in teams with a high network level centralization, reciprocity between core central players predicts individual level performance. Perhaps when a network is less centralized, on the other hand, the frequency of triadic passing relationships predicts individual performance. It is important to consider how broader, team-level network metrics can impact which node-level
metrics are likely to contribute to performance of core players. Once I identified the node-level metrics that predict “coreness” based on performance, I further examined the ways in which network (i.e., team)-level metrics influenced the success of core players. This helped to isolate how players with strong node-level performance metrics were helped or hindered by the dynamics of their teammates. I examined the interaction between aggregated average team-level social network metrics and PIE for the most valuable player on each team (player with highest average PIE score across the season).

Table 3

Research Questions and Potential Outcomes

<table>
<thead>
<tr>
<th>Research Question</th>
<th>Potential outcomes</th>
</tr>
</thead>
</table>
| RQ1: How can we best define the strategic core of the team in question? | 1a. Players with the highest centrality scores tend to be the most valuable players  
1b. Players with the highest centrality scores are not the most valuable players |
| RQ2: Is the strategic core consistent across teams? | 2a. Yes – players in positions that facilitate more contact with the ball tend to be core players (e.g., small forward)  
2b. No – coreness is highly dependent on broader team-level network structures and is not dependent on a player’s position |
| RQ3: Does the strategic core of a team change over the season? | 3a. No – across performance episodes the same players tend to comprise the core  
3b. Yes – from game to game, the core of the same team is comprised of different players |
| RQ4: How does the overall team on networks affect the contributions of core players? | 4a. Centralized networks will have a larger impact on player performance  
4b. Decentralized networks will have a weaker impact on player performance |
Method

The current study utilized data captured from the 30 basketball teams playing in the National Basketball Association (NBA) to examine team structures, with respect to team roles. The current study explores the application of network analyses for the purposes of defining and measuring the strategic core of NBA teams and how the interactions involving core players differentially impact team performance. I explored the characteristics of coreness apart from direct contributions to performance to inform an understanding of how interactions of the core impacted performance measures. To answer these exploratory questions, both process and outcome data were used.

Data Collection

Process and outcome data were collected using two methodologies: manual coding and web scraping. The process data was constructed using manually coded passing data. Manually coded data were obtained by observing game play and coding player interactions by hand. I scraped performance data by extracting player performance metrics from websites that feature basketball performance statistics (NBA Media Ventures, LLC, 2020; Sports Reference, LLC, 2020). The player and team performance outcome data were web scraped from the National Basketball Association and sports reference statistics (NBA Media Ventures, LLC, 2020; Sports Reference, LLC, 2020).

Manual Coding

Data were collected by recording the passing interactions of 486 NBA players (basketball-reference.com) present across all basketball games that occurred in the 2016-2017 NBA season. Team process data were obtained by manually coding the passing sequences of all 1,309 games played in the 2016-2017 NBA season. Over seventy undergraduate and graduate
students were recruited from DePaul University to manually code all player interactions. Undergraduates were trained on how to properly record passing sequences, actions taken by players, and relevant game events (see Table 4 for the code book). Four undergraduate and six graduate students reviewed the coding and removed errors. These data were compared with box score data (the summary of the results of the game) obtained by the NBA to ensure accuracy of coding.

**Data Cleaning**

Once all 1,309 games were manually coded the data were evaluated for errors. A list of permissible codes was generated, and all games were examined for codes not included in the permissible code list. Permissible codes consisted of jersey numbers used by players during the 2016-2017 NBA season and all acceptable abbreviated codes used to note player actions (see Table 3). A game needed to be cleaned if it contained either an incorrect player jersey number or a code that was not contained in the list of acceptable codes (e.g., FMT, FGMX, X). At the start of cleaning there were 1,006 games that contained at least one error. Data cleaning concluded on December 30, 2020 at which time a total of 80 games (6.11% of all games) contained at least one incorrect code.

**Table 4**

*Abbreviations and Descriptions of Acceptable Codes Used to Note Results*

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBT</td>
<td>Dead ball turnover (change of possession from: ball out of bounds on offensive team, offensive foul, offensive lane violation)</td>
</tr>
<tr>
<td>LBT</td>
<td>Live ball turnover</td>
</tr>
</tbody>
</table>

(continued)
Table 4 (continued)

Abbreviations and Descriptions of Acceptable Codes Used to Note Results

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FGM2</td>
<td>2-point field goal made</td>
</tr>
<tr>
<td>FGM3</td>
<td>3-point field goal made</td>
</tr>
<tr>
<td>ORB</td>
<td>Offensive rebound</td>
</tr>
<tr>
<td>DRB</td>
<td>Defensive rebound</td>
</tr>
<tr>
<td>TO</td>
<td>Time-out</td>
</tr>
<tr>
<td>FGA2</td>
<td>2-point field goal attempt missed</td>
</tr>
<tr>
<td>FGA3</td>
<td>3-point field goal attempt missed</td>
</tr>
<tr>
<td>OB</td>
<td>Out of bounds, but no turnover</td>
</tr>
<tr>
<td>FTM</td>
<td>Free throws made (followed by how many made; ex. 0, 1, 2, 3)</td>
</tr>
<tr>
<td>JB</td>
<td>Jump Ball</td>
</tr>
<tr>
<td>LB</td>
<td>Loose Ball</td>
</tr>
<tr>
<td>PF</td>
<td>Personal Foul (for fouls that did not lead to free throw attempts)</td>
</tr>
<tr>
<td>FF</td>
<td>Flagrant Foul (followed by a 1 or 2; ex. FF1-player remains in game; FF2-player ejected from game)</td>
</tr>
<tr>
<td>TF</td>
<td>Technical Foul</td>
</tr>
</tbody>
</table>

Web scraping

Web scraping was used to obtain performance metrics and other data (e.g., jersey number, court position, player name) for all NBA players and teams for all games considered. Web scraping involves using a coding script to extract information (e.g., tables and calculations) from public websites. In this case, a programming script (Braun, Kuljanin & DeShon, 2017) was used to harness data from www.nba.com and www.basketball-reference.com including all traditional and advanced statistics capturing player outcomes (NBA Media Ventures, LLC, 2020; Sports Reference, LLC, 2020). Player names, positions, and jersey numbers were downloaded from basketball-reference.com/leagues/NBA_2017_advanced.tml (Sports Reference, LLC,
One advanced metrics were web scrapped to aid in measuring player performance: player impact estimate (PIE) (NBA Media Ventures, LLC, 2020). Next I will discuss how data used to calculate PIE metrics were web scraped, how the data were harnessed and used to calculate the metric of interest for analyses. To calculate PIE scores, box score data were web scraped by importing data from basketball-reference.com/boxscores/ using the game ID number and the team’s name. This website contains full score data for each plater on both the home and away team for every game. For each player in every game, the following data are provided: number of minutes played (MP), number of field goals made (FG) and attempted (FGA), field goal percentage (FG%), number of 3-point field goals made (3P) and attempted (3PS), 3-point percentage (3P%), number of free throws made (FT) and attempted (FTA), free throw percentage (FT%), number of offensive rebounds (ORB), defensive rebounds (DRB), total rebounds (TB), number of assists (AST), steals (STL), blocks (BLK), turnovers (TO), personal fouls (PF), total points scored (PTS), and “plus/minus” (+/-) (which is a net indicator of number of points the players team scored less points scored by the opponent while he was on the court during each quarter). These data were scraped and saved to a data table that captures the team’s name and players name along with each of the metrics listed above. Next, the PIE score was calculated for each player for each game. Because a player’s PIE score represents the relative contribution of that player to overall team performance based on overall team-level outcomes (e.g., points, field goals made, etc.) (NBA Media Ventures, LLC, 2020) the PIE scores are calculated as follows:

$$\text{PIE} = \frac{\text{PTS} + \text{FGM} + \text{FT} - \text{FGA} - \text{FTA} + \text{DRB} + (0.5)\text{ORB} + \text{AST} + \text{STL} + (0.5)\text{BLK} - \text{PF} - \text{TOV}}{(\text{Team-Level): PTS} + \text{FGM} + \text{FT} - \text{FGA} - \text{FTA} + \text{DRB} + (0.5)\text{ORB} + \text{AST} + \text{STL} + (0.5)\text{BLK} - \text{PF} - \text{TOV}}$$

In addition to the above-mentioned metrics each player's formal position on the team was considered to account for his formal role on the team (NBA Media Ventures, LLC, 2020).
**Data Wrangling**

First, a spreadsheet that contained the cleanest version of all passing sequences for every single game was imported into R (R Core Team, 2019). Next, the identification numbers used to differentiate each NBA game and the historical date for each game was imported. These two spreadsheets were joined such that each game was linked with the correct identification number from the original coding spreadsheet and the historical date of game play. To select only regular season games for analysis, games were filtered to exclude games that were played after April 14, 2017 (the last day of the regular 2016-2017 season). This new data file contained 1,309 unique games in total. Next, the pass sequences were split into a new column that contained a new row for each string in the pass sequence (e.g., if the first pass sequence contained 17-24-4-8-FGM2, five new rows were generated in this new column: 17, 24, 4, 8 and FGM2, respectively. The next step was to isolate *only passes* between players.

To identify passes between players a new column was created by duplicating the passing sequences column and shifting it up one row. This lead-shifted column was used to capture the passes and properly label the “sender” and “receiver” within each passing sequence. In the sequence described above, the lead-shifted column contained: 24, 4, 8, FGM2 and *Not Applicable*. To isolate *only* the passing interactions a third column was created. A decision rule was created to input a 1 (count) in the newly created pass column when both the sender and receiver column contained numeric data (jersey numbers only) and a 0 (no count) when an action or *NA* was present in either column. This decision rule effectively captured only pass sequences between players and omitted player actions from the newly created variable. This variable also served as a count that could inform the weighted edge lists that were needed to create the passing network visualizations and calculate player and network level social network metrics.
An “edge list” is a record of each dyadic interaction between all players that occurred during one game. This edge list identifies the “sender” and “receiver” of the ball during the game in order to inform the network analysis that displays a directional visual representation of the network. Weighted edge lists were created by counting the number of times a 1 was recorded in the “pass” column within each game for each team between each pair of players. The players or jersey numbers on each team were identified by isolating all the distinct jersey numbers that were recorded within each game for each team across all passing sequences. The edges (counts of passes between players) and nodes (players) for every regular season game were saved as objects to be used to generate network metric visualizations and calculate player and team level network metrics for every game.

Data from the manual coding and web scraping was then combined using data wrangling in R (R Core Team, 2019). This is a way to transform the data into a usable format by combining passing data and outcome data into a shared data frame. Additionally, data wrangling aids in aggregating interactions across the season at both the individual player and team levels depending on the level of analysis being considered.

**Constructing Social Networks**

**Passing Networks**

Social networks are a visual representation of the team interactions that occurred during the time frame of interest. The original data sheets (one for each of the 1,309 games) contain 3 columns of data: possession, team, and pass sequence (see Figure 1). The number of rows varies because each row of data represents a possession which changes from game to game. For example, a game was played between the New York Knicks and the Cleveland Cavaliers on October 25, 2016. At the start of the game the first row contains a 1 in the first column, NYK in
the second column, and the following sequence of passing data in the third column: JB-25-7-6-5-13-25-FGM2. This indicates that the game started with a jump ball, number 25 on the New York Knicks obtained the ball, passed to player number 7, who passed to player 6, then 5 and so on. The possession ended when player number 25 successfully made a 2-point field goal. The next possession would be labelled as 2 in the first column (because it would now be the second possession of the game), CLE in the second column (Cleveland would then obtain possession of the ball), and the third column would list the sequence of passes and actions carried out by the Cavaliers.

An edge list is created for each team by separating all passing sequences in each possession into dyadic data and identifies the “sender” and “receiver” of each pass in a separate column (See Figure 1). Once dyadic relationships have been captured, this data is fed into an adjacency matrix or a “sociomatrix.” A sociomatrix is a data frame that lists each player in the rows and lists the number of times he passed to every other player (listed across the columns). These data are then used to create visual representations of all players passing interactions across one game for the entire team (see Figure 3). Visualizing data in this way is helpful in assessing which actors are dominating team processes. In Figure 3, for instance, it becomes apparent that player number 30 is highly central to the team (he is featured prominently in the analysis and many incoming and outgoing passes can be seen). To a lesser extent, players 35, 11, and 23 are also highly central (or dominant) in this passing network.

Analyses

Social Network Analyses

I compared the core structure of each of the 30 NBA teams by visually inspecting the social networks created using the passing interactions between players. I created frequency
distributions for each team to compare the number of players on each team that have above average scores on node-level indicators of high interaction. In this way, I could inspect patterns that emerged for evidence indicating a typical pattern across teams (e.g., number of players, formal roles). In addition, by regressing each of the node level network metrics (e.g., centrality, reciprocity, etc.) on seasonal individual level performance data (i.e. average PIE score) I identified the node-level metrics that were predictive of core membership. Subsequently, I compared the players identified as belonging to the core of each team to detect whether players that occupy the same position are likely to comprise the strategic core across teams. In other words, I assessed whether formal positions on each team were predictive of core membership.

By calculating the node-level social network metrics associated with the passing networks for each team and regressing them on PIE for each player, I isolated the node-level centrality measures that are the best predictors of core players on each team across the season. This aided in identifying is how core players operate in this context. This approach informed my understanding of how node (i.e. player)-level SNA metrics predicted player success. This helped isolate the extent to which team processes influence the execution of valued behavioral outcomes.

**Profile Analysis**

Profile analysis is a multivariate technique that allows for repeated measures (Desjardins & Bulut, 2017). Profile analysis is a multivariate analysis of variance that incorporates repeated measures. While this approach is typically used to compare assessment scores, it is useful because it involves tracking the variation of scores obtained by the same individual across separate performance episodes. This enables the calculation of a kind of longitudinal reliability
score or the creation of a “profile” for each subject that can then be tracked and compared over multiple performance episodes.

Profile analysis can be used to graphically represent change in “coreness” of players in each team across the NBA season. Profile analysis was used to graphically represent the “pattern” or the reliability of coreness scores for players in each team across the season. Graphs were created and visually inspected for each team. Each a player’s composite coreness score can be visually inspected across games and compared between players. This can help to determine how much variation in coreness exists within and between players based on team membership.

**Results**

**Statistical Data Summary Overview**

**Research Question 1: How Can the Strategic Core of Teams be Measured?**

Two approaches were taken to investigate how to define the strategic core of teams using the current data. The first approach was to examine the “coreness” score of all players independent of team membership across the entire NBA season. The second approach was to examine core membership of each player within their respective team. I discuss each approach in the next section.

To accomplish the first approach, I chose to correlate all player’s composite “coreness” metric with aggregated mean PIE scores to ascertain the strength and direction of the relationship between players “coreness” score and performance. To accomplish this, I computed a mean PIE score for all players across all games and a composite “coreness” score using the mean of all player-level centrality metrics: closeness, betweenness, in-degree, and out-degree. Each centrality measure was equally weighted to create the composite coreness score. I will refer to this as “coreness” hereafter. A significant strong positive correlation was found between players
coreness and performance across games, $r (324) = 0.633, p < .001$. This indicates that as a player’s coreness value increases, his relative contribution to team performance also increases. The magnitude of the correlation is strong, given that coreness explains about 40% of the variance in a player’s relative performance irrespective of team membership.

Next, players were grouped by team membership to further explore the relationship between coreness and PIE scores. The correlation between all players’ coreness scores and the average PIE score were computed for each team. Table 5 reports the correlation coefficients between coreness and average PIE score for all teams across the season.

Table 5

*Correlation between coreness and average PIE scores for all NBA teams*

<table>
<thead>
<tr>
<th>Team</th>
<th>Coefficient</th>
<th>Team</th>
<th>Coefficient</th>
<th>Team</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATL</td>
<td>0.564***</td>
<td>HOU</td>
<td>0.797***</td>
<td>OKC</td>
<td>0.814***</td>
</tr>
<tr>
<td>BKN</td>
<td>0.670***</td>
<td>IND</td>
<td>0.809***</td>
<td>ORL</td>
<td>0.726***</td>
</tr>
<tr>
<td>BOS</td>
<td>0.893***</td>
<td>LAC</td>
<td>0.605***</td>
<td>PHI</td>
<td>0.528***</td>
</tr>
<tr>
<td>CHA</td>
<td>0.652***</td>
<td>LAL</td>
<td>0.362***</td>
<td>PHX</td>
<td>0.528***</td>
</tr>
<tr>
<td>CHI</td>
<td>0.812***</td>
<td>MEM</td>
<td>0.695***</td>
<td>POR</td>
<td>0.924***</td>
</tr>
<tr>
<td>CLE</td>
<td>0.844***</td>
<td>MIA</td>
<td>0.305***</td>
<td>SAC</td>
<td>0.762***</td>
</tr>
<tr>
<td>DAL</td>
<td>0.447***</td>
<td>MIL</td>
<td>0.712***</td>
<td>SAS</td>
<td>0.561***</td>
</tr>
<tr>
<td>DEN</td>
<td>0.333***</td>
<td>MIN</td>
<td>0.687***</td>
<td>TOR</td>
<td>0.745***</td>
</tr>
<tr>
<td>DET</td>
<td>0.162***</td>
<td>NOP</td>
<td>0.664***</td>
<td>UTA</td>
<td>0.475***</td>
</tr>
<tr>
<td>GSW</td>
<td>0.792***</td>
<td>NYK</td>
<td>0.669***</td>
<td>WAS</td>
<td>0.777***</td>
</tr>
</tbody>
</table>

*** $p < .001$
All correlations were statistically significant at the p < .001 level. These correlations indicate that the relationship between coreness and each player’s relative performance within each team is both significant and universally positive (as coreness increases, player relative performance increases) across teams. Interesting to note, however, that the magnitude of the relationship varied widely depending on which team is considered. For example, the correlation between players average coreness scores and PIE scores for the Detroit Pistons is weak (r = 0.162, p<.001), with an R-squared of 0.026. This indicates that for the players on the Pistons, coreness scores explain a mere 2 to 3% of the variance in player’s relative performance. In considering the Portland Trail Blazers, on the other hand, the correlation between coreness and PIE was very strong (r = .924, p <.001), with an R-squared of 0.854. For the Trail Blazers, coreness scores explained 85% of the variance in player’s relative performance. Using a rough guideline to interpret the correlations (assuming any correlation above 0.5 is meaningful), for 24 of the 30 teams (i.e., ATL, BKN, BOS, CHA, CHI, CLE, GSW, HOU, IND, LAC, MEM, MIL, MIN, NOP, NYK, OKC, ORL, PHI, PHX, POR, SAC, SAS, TOR, WAS) coreness explained a large amount of the variance in player’s relative contributions to performance. For the remaining 6 teams, coreness was only weakly, albeit significantly, related to player’s relative performance (i.e., DAL, DEN, DET, LAL, MIA, UTA). Interestingly, teams with higher correlations between players coreness and PIE had higher team performance than teams with lower correlations. Table 6 shows overall team rankings for the 2016-2017 season. It is noteworthy that the five highest ranked teams (e.g., BOS, CLE, GSW, HOU, SAS,) also had strong correlations between coreness and players relative contribution, while teams with weaker correlations tended to have lower team performance (e.g., DEN, DET, DAL, LAL, MIA).
Table 6

Team Standings for the 2016-2017 Season

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team</th>
<th>Rank</th>
<th>Team</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>GSW</td>
<td>16</td>
<td>POR</td>
</tr>
<tr>
<td>2</td>
<td>SAS</td>
<td>17</td>
<td>MIA</td>
</tr>
<tr>
<td>3</td>
<td>HOU</td>
<td>18</td>
<td>DEN</td>
</tr>
<tr>
<td>4</td>
<td>BOS</td>
<td>19</td>
<td>DET</td>
</tr>
<tr>
<td>5</td>
<td>CLE</td>
<td>20</td>
<td>CHA</td>
</tr>
<tr>
<td>6</td>
<td>LAC</td>
<td>21</td>
<td>NOP</td>
</tr>
<tr>
<td>7</td>
<td>TOR</td>
<td>22</td>
<td>DAL</td>
</tr>
<tr>
<td>8</td>
<td>UTA</td>
<td>23</td>
<td>SAC</td>
</tr>
<tr>
<td>9</td>
<td>WAS</td>
<td>24</td>
<td>MIN</td>
</tr>
<tr>
<td>10</td>
<td>OKC</td>
<td>25</td>
<td>NYK</td>
</tr>
<tr>
<td>11</td>
<td>ATL</td>
<td>26</td>
<td>ORL</td>
</tr>
<tr>
<td>12</td>
<td>MEM</td>
<td>27</td>
<td>PHI</td>
</tr>
<tr>
<td>13</td>
<td>IND</td>
<td>28</td>
<td>LAL</td>
</tr>
<tr>
<td>14</td>
<td>MIL</td>
<td>29</td>
<td>PHX</td>
</tr>
<tr>
<td>15</td>
<td>CHI</td>
<td>30</td>
<td>BKN</td>
</tr>
</tbody>
</table>

*Note. Team rankings based on expanded standings based on win-loss record per team. Rankings obtained from Sports Reference, LLC (2020.)*

Research Question 2: Is the Strategic Core Consistent Across Teams?

To investigate whether the strategic core was consistent across teams, I began by comparing the means and standard deviations of the composite coreness metric across the five positions (center, power forward, point guard, small forward and shooting guard). Table 7 summarizes these findings.

Table 7

Means and SDs Based on Player Position

<table>
<thead>
<tr>
<th>Position</th>
<th>Mean</th>
<th>SD</th>
<th>Observations (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center (C)</td>
<td>6.282</td>
<td>3.407</td>
<td>4528</td>
</tr>
<tr>
<td>Power Forward (PF)</td>
<td>6.917</td>
<td>2.932</td>
<td>4498</td>
</tr>
<tr>
<td>Point Guard (PG)</td>
<td>11.574</td>
<td>3.648</td>
<td>4336</td>
</tr>
<tr>
<td>Small Forward (SF)</td>
<td>7.352</td>
<td>3.272</td>
<td>4143</td>
</tr>
<tr>
<td>Shooting Guard (SG)</td>
<td>8.174</td>
<td>2.587</td>
<td>4799</td>
</tr>
</tbody>
</table>

To examine whether group differences of this size were meaningful, an analysis of variance (ANOVA) model was generated using player position as the grouping variable and
composite coreness as the dependent variable. There was a significant effect of position type on composite coreness score at the p < .000 level for the five positions [F (4,22299) = 1877, p < .001] (See Table 8). The significant ANOVA model indicates that belonging to a specific position within a team has a meaningful impact on a player’s coreness score. To further explore these differences, post-hoc tests were run on the analysis of variance. Post-hoc tests allow us to test how meaningful group differences are with more specificity. For instance, it is unclear from the means in Table 6 whether the coreness scores for players who are centers (mean = 6.282, SD =3.407) are meaningfully different from players who are in the position of power forward (mean = 6.917, SD = 2.932). It is also unclear whether coreness scores for players in those positions are meaningfully different from player who are small forwards, etc. While the ANOVA results indicate differences between groups exist, a post-hoc test allows for a finer-grained analysis of where they exist, and which groups’ means are meaningfully different from each other.

Tukey’s honestly significantly different post-hoc test was used to analyze whether the mean coreness scores for each position were significantly different each other (Table 9). Table 9 summarizes the mean difference between groups in the form of pairwise comparisons which evaluates the differences between each position and every other position. For example, the first row indicates that the mean coreness score of players in the position of power forward is 0.634 points higher than players who are in the center position. The 95% confidence interval contains the estimated range of values for this difference in the population and since this range does not contain zero, it supports the idea that the difference in scores is different from zero. The next row reveals the difference between point guard and center (the positions with the highest and lowest coreness scores, respectively). Table 9 shows that on average, point guards have a coreness score that is 5.292 points higher than centers. The chart displays the differences in
scores between all positions. It’s worthwhile to note that differences are largest between point guards (which have the highest mean coreness value) and positions with low coreness values (e.g., centers, power forwards, small forwards). The mean difference is positive if the position listed first in the pair has a higher value than the position listed second. Negative values indicate that the position listed first has a lower coreness value than its paired position (e.g., small forwards are 4.222 lower than that of point guards).

**Table 8**

*Analysis of Variance in Coreness Based on Player Position*

<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>Df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pos Residuals</td>
<td>75875</td>
<td>4</td>
<td>22299</td>
<td>18969</td>
<td>&lt;.001***</td>
</tr>
<tr>
<td></td>
<td>22537</td>
<td>22299</td>
<td>10</td>
<td>1877</td>
<td></td>
</tr>
</tbody>
</table>

*p<.05; **p<.01; ***p<.001

**Table 9**

*Tukey’s Honest Significance Post Hoc Test for Between-Group Differences in Coreness Based on Player Position*

<table>
<thead>
<tr>
<th>Position Comparison</th>
<th>Mean Difference</th>
<th>95% Confidence Interval for Mean Lower Bound</th>
<th>95% Confidence Interval for Mean Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td>PF-C</td>
<td>0.634***</td>
<td>0.452</td>
<td>0.827</td>
</tr>
<tr>
<td>PG-C</td>
<td>5.292***</td>
<td>5.108</td>
<td>5.476</td>
</tr>
<tr>
<td>SF-C</td>
<td>1.070***</td>
<td>0.884</td>
<td>1.260</td>
</tr>
<tr>
<td>SG-C</td>
<td>1.892***</td>
<td>1.712</td>
<td>2.071</td>
</tr>
<tr>
<td>PG-PF</td>
<td>4.648***</td>
<td>4.473</td>
<td>4.842</td>
</tr>
<tr>
<td>SF-PF</td>
<td>0.436***</td>
<td>0.249</td>
<td>0.622</td>
</tr>
<tr>
<td>SG-PF</td>
<td>1.257***</td>
<td>1.077</td>
<td>1.437</td>
</tr>
<tr>
<td>SF-PG</td>
<td>-4.222***</td>
<td>-4.410</td>
<td>-4.033</td>
</tr>
<tr>
<td>SG-PG</td>
<td>-3.400***</td>
<td>-3.582</td>
<td>-3.219</td>
</tr>
<tr>
<td>SG-SF</td>
<td>0.822***</td>
<td>0.638</td>
<td>1.006</td>
</tr>
</tbody>
</table>

*p<.05; **p<.01; ***p<.001
**Research Question 3: Does the Core of a Team Change Over the Season?**

A profile analysis was used to create a longitudinal reliability score. This allowed for an investigation of how players’ coreness changed across games in the season. To generate a graph for each team, four players were chosen based on consistency of play (players who appeared together in the largest number of games per team were chosen to facilitate comparison). Players were compared across 25 games. This allowed for a representative sample of how player’s coreness varied across the season within the same team.

For example, Figure 4 features a profile plot for the Atlanta Hawks. Four key players (Dennis Schroder, Dwight Howard, Paul Millsap, and Tim Hardaway) were chosen because these players tended to be present within the same games. These players fit the criteria because they appeared together in the largest number of games across the season, facilitating the largest sample of games to draw from for comparison. Figure 4 represents how each of the four players’ coreness varied across performance episodes within the Atlanta Hawks. Dennis Schroder, a point guard on the team, tended to have the highest coreness score across the most games, although the line that represents his coreness metric crosses Paul Millsap’s on five occasions over the course of the 25 games represented. Paul Millsap, a power forward, consistently had the next highest coreness score across all the games included in the analysis. Tim Hardaway, a shooting guard, tended to have lower scores than the previous two players across games, although his coreness line crosses with Dwight Howard ten times, indicating that there is more variability in coreness for these two players or players who occupy those positions. Dwight Howard, a center, had the lowest score (See Figure 4). Figures 4 through 34 provide a visual representation of the variance in coreness scores for selected players for each of the 30 teams in the NBA (Appendices contain...
the profile analysis graphics for each team in the data set which are numbered alphabetically by team name).

These plots shed light on the variability of coreness scores within individual players and between players over time. Consider the graph for the Golden State Warriors (Figure 13). The profile plot provides a visual indication of the stability of each players coreness score across multiple games. It is clear to see in this graph that players scores do tend to fluctuate somewhat, but clear patterns are present in terms of each players coreness in relation to other players. For example, it’s clear that Stephen Curry (point guard) and Draymond Green (power forward) consistently retain the highest coreness scores compared to the two other players. Next highest in coreness ranking is Andre Iguodala (small forward) and the lowest score is attributed to Zaza Pachulia (center). This is relatively consistent with what we might expect (except for the power forward scoring higher on coreness than a small forward on this team, for this set of games).

While the lines do intersect (especially between Stephen Curry and Draymond Green) there seems to be clear separation between players. We can easily identify which players have higher coreness values (e.g., Stephen Curry and Draymond Green) and which players tend to consistently score lower (e.g., Andre Iguodala and Zaza Pachulia)

A similar pattern can be found for another highly successful team, the San Antonio Spurs (Figure 30). As this graph indicates Kawhi Leonard (small forward) emerges as consistently having the highest coreness score among the players selected. Next highest coreness can be attributed to Danny Green (shooting guard). There does appear to be quite a bit of intersectionality between the last two players, Dewayne Dedmon (center) and Davis Bertans (power forward). These patterns seem somewhat consistent with what would be expected based on position, and again there is clear separation between players.
A key takeaway in viewing the profile plots of higher ranked (i.e., winning) teams is that there appears to be a consistent core structure. In other words, there tends to be one or two dominant players on these teams, with high coreness scores relative to other players, with a clear separation between these core, dominant, players and the supporting players on the team. The same pattern was not apparent in lower-ranked teams, as I will discuss next.

The profile plot for the Brooklyn Nets (a lower-ranked team in terms of winning) had much more intersectionality between players across the sample of games selected. Consider Figure 5. On the Nets, Brook Lopez (center) appears to have the highest coreness score across the games selected, it is difficult to interpret who among the remaining players Chis LeVert (small forward), Isaiah Whitehead (point guard), and Randy Foye (shooting guard) has the next highest score. There appears to be less separation among the players scores and more overlap and variability.

Another lower ranked team in terms of winning, the Los Angeles Lakers, also had greater variability in their profile plots (see Figure 17). Brandon Ingram (small forward), Jordan Clarkson (shooting guard), Nick Young (shooting guard) and Timofey Mozgov (center) all have a great deal of variability in their coreness scores across games. The line representing each player’s coreness scores crosses other players multiple times across games. As can be seen in Figure 17, it is difficult to determine which player on the Los Angeles Lakers has the highest coreness score and there is little consistency between players across the sample of games selected.

Research Question 4: How Does the Overall Team Network Affect Contributions of Core Players?

To investigate the impact of team-level network metrics on players team contribution, I correlated the mean network metrics for each team with the most valuable player’s PIE score.
First, I averaged all team-level network metrics across all games, computing 30 sets of team-level network metrics (one for each of the 30 teams). Then, I grouped all players by team, sorting by PIE score, to select the player with the highest score (most valuable player). I correlated the PIE scores for the most valuable player on each team with all team’s aggregated metrics to examine the impact of team level metrics on the contributions of core players. A summary of the findings is below in Table 10.

Table 10

Pearson Correlations Between Top Players PIE scores and Team Network Metrics

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. PIE score</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Density</td>
<td>-0.254</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Centralization</td>
<td>0.387*</td>
<td>-0.541**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Transitivity</td>
<td>-0.229</td>
<td>0.944***</td>
<td>-0.502**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Diameter</td>
<td>-0.106</td>
<td>-0.819***</td>
<td>0.132</td>
<td>-0.743***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Distance</td>
<td>0.114</td>
<td>-0.954***</td>
<td>0.463**</td>
<td>-0.901***</td>
<td>0.901***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Reciprocity</td>
<td>-0.412*</td>
<td>0.774***</td>
<td>-0.484**</td>
<td>0.766***</td>
<td>-0.510**</td>
<td>-0.710***</td>
<td></td>
</tr>
</tbody>
</table>

*p<.05; **p<.01; ***p<.001  n = 30

There was a significant positive weak-to-moderate correlation between most valuable players PIE score and Centralization at the p <.05 level, r (30) = 0.387, p <.05. In addition, there was a significant strong negative moderate correlation between team reciprocity and the most valuable player’s PIE score was also significant at the p <.05 level, r (30) = -0.412, p <.05. These correlations indicate that the higher team-level centralization scores (i.e., the more passing interactions are dominated by a smaller subset of players), the higher the most valuable player’s PIE scores were. This is intuitive in that the more a team is dominated by a handful of players, the higher the top player’s relative contribution to team outcomes. On the other hand, the negative correlation between reciprocity and the top players PIE score indicates as reciprocal dyadic passing interactions on a team increased, the top players PIE score decreased. This
indicates that as dyadic passing relationships increased, the dominant players relative
collection to team outcomes decreased (ostensibly because teammates had possession of the
ball and were contributing more to team outcomes).

Discussion

Conceptual Review of Results

Results of the current study revealed that ignoring team membership, coreness was
significantly positively correlated with PIE scores. This correlation was moderate when
examined irrespective of teams, but varied greatly when examined within teams. This indicates
that, generally, players with higher composite coreness scores (as calculated from social
network metrics) contributed a higher proportion of game events than players with low coreness
scores. However, team dynamics appear to impact the relationship between coreness and PIE.

Player position is an important consideration in contextualizing social network metrics.
Point guards have the highest coreness score, followed by shooting guards and small forwards.
Players in the power forward and center position appear to have lower coreness score. Each
position has a significantly different coreness score from every other position.

By examining profile plots, it became apparent that winning teams tended to have a more
structured core than teams that were lower ranked. Highly ranked teams had graphs with one or
two dominant players, and less variability in coreness scores within and between players. Lower
ranked teams had graphs with large swings in coreness scores within and between players, and
no identifiable pattern or structure to the core of the team.

Finally, network metrics did play a role in impacting how core players contributed to
team outcomes. The more centralized a teams network was, on average, the better core players
performed. On the other had, teams that had more reciprocity (more mutual connections) tended
to be detrimental to core players.
The current study provided evidence that centrality scores derived from social network analysis predict performance (PIE) of NBA players. In fact, a composite coreness score derived for 324 NBA players had a strong positive relationship with players season-level PIE scores. Considering this metric independently of teams, coreness accounted for about 40% of the variance in player-level performance across the season. When the relationship was broken out by team, the relationship between coreness and player-level performance varied widely ($r$ ranged from .162 to .924), but the relationship between player coreness scores and PIE was statistically significant for all NBA teams (See Table 4). This means that players who were more interactive on the team (had possession of the ball more often) had a greater impact on the team’s performance. In other words, players that are more central or “core” tended to perform better in terms of the proportion of game events that contributed to the overall team score.

Player position plays a key role in determining coreness and performance. Of the five court positions, point guard had the highest coreness score, followed by shooting guard, small forward, power forward, and lastly center. Each of these positions had coreness scores that were significantly different from each other (see Tables 6-9). Teams with highly centralized players in key roles (e.g., point guard, shooting guard, small forward) and less core players in supporting roles (e.g., power forward, center) tended to perform better. The teams who performed less effectively tended to have a lot of variation in coreness within and between players.

The profile plots enabled the examination of how player’s coreness scores varied across games. Not surprisingly, the profile plots echoed the findings of the ANOVA generally, in that players in the point guard position tended to have higher coreness scores across games than players who were in the positions of power forward of center. The profile analyses revealed that players on certain teams tended to have fairly stable coreness score across the season (e.g.,
Cleveland Cavaliers, Memphis Grizzlies, Miami Heat, Phoenix Suns), while for other teams, players scores were quite variable (e.g., Denver Nuggets, Detroit Pistons, Los Angeles Lakers, Milwaukee Bucks). This indicates that teams with players whose coreness scores were more consistent tended to perform better than teams whose players scores were not consistent. It appears that this is a function of team membership as well, with coreness being more vital to positions that are more interactive (e.g., point guard, shooting guard, small forward) than for positions that are less interactive (e.g., center, power forward).

Lastly, two network-level metrics had significant influences on the PIE scores of top players. Network level centralization boosted the performance of top players, while team-level reciprocity had a moderate negative impact on player level performance of top players. Essentially, the more centralized a team network was, the better it was for top players (who likely drove up the centralization score of the team), while reciprocity (more dyadic team interactions) hampered the performance of top players (See Table 10). This indicates that teams that were more centralized tended to be more beneficial for the most skilled players on that team. As a team’s dyadic interactions increased, this tended to negatively impact the contributions of core players.

These findings indicate that for team play, it is essential to have the most highly skilled players in key functions. This is in alignment with the literature on role theory which asserts that some roles are more impactful than others to team performance because they are integral to the flow of information (Humphrey, 2008) or are exposed to more organizational problems (Barker, 1993). Upon considering basketball teams it appears that certain roles are key to both player-level performance (PIE) and team outcomes.
Consistency appears to be a key factor with respect to the most highly successful basketball teams. This echoes the emphasis placed in the teams literature on understanding the function of each role on highly interdependent teams, focusing on selection for key roles, and standardization (Sundstrom, 1990). The most successful teams appeared to be those who had the strongest players in more aggressive roles, allowing them to dominate game play, while supporting roles tended to have consistently lower coreness. This separation, or division of labor, appeared to drive team success.

**Implications for Theory**

This research focused on the ways in which dynamic interactions between team members inform outcomes. First, it was a departure from more traditional models (such as the IPO framework; Hackman, 1987; McGrath, 1964) in that it measured dynamic interactions between players on a team. In addition, the current study added much in the way of further understanding the importance of roles to team performance outcomes (Kozlowski & Klein, 2000). This work is a vital first step in answering the recent call for more research on team processes that measure the patterns of interactions within teams (Crawford & LePine, 2013). In considering roles, the current work also elucidated a potentially new implication: consistency within roles as a potentially factor in team effectiveness. And lastly, the current work highlighted the dynamic and recursive impact of individual performance on team performance. I will discuss each of these implications next.

The results of the current study provide additional evidence that the dynamic nature of team processes requires consideration at multiple levels of analysis. Utilizing dynamic interactive data can aid us in understanding how the dynamics between team members play out as a function of individual performance within specific roles. The teams literature emphasizes the
importance of properly staffing and standardizing each role within teams to enhance team
effectiveness (Mumford, Van Iddekinge, Morgeson & Campion, 2008; Steiner, 1972). The
current study adds to this by providing insights into how team interactions influence individual
and team-level performance interact and the ways in which roles can influence the inputs of each
team member in a highly interactive team.

This study was a departure from the study of inputs, mediators and outputs in the study of
team interactions because it did not measure these variables as static constructs but utilized
dynamic interactions to attempt to demystify how unique contributions of team members
contributes to team outcomes. This study implemented cutting-edge approaches (e.g., in
employing SNA and profile analysis) that view players inputs as dynamic metrics derived from
their moment-by-moment interactions and analyzing them at multiple levels: the player level, the
team level, and within and between roles. Recent work by Crawford and LePine (2013) called
for work that studies different elements of team structure such as level of interconnectedness,
centralization, and the extent of specialization within teams. The current work provides one
approach to understanding how team process elements at these levels contribute to individual
and team-level outcomes. In addition, profile plots allowed the exploration of how player
contributions changed over time within their team and allowed for a high-level comparison of
how these metrics changed over time.

The current research adds to our knowledge of the importance of roles to team outcomes.
Kozlowski and Klein (2000) discussed the importance of roles in establishing task expectations
for team members and providing a guiding framework for the pattern of interactions for effective
teamwork. This is evident in our findings as it was clear that certain roles were more important to
team outcomes than others in considering the pattern of team interactions and player’s relative
contributions. These results not only echo the literature that suggests that certain roles are more important to team outcomes in applied settings (Belbin, 1993; Lawrence & Lorsch, 1969; Mumford, Campion & Morgeson, 2006; Mumford et al., 2008) but also suggests that consistency within core roles is also of great import. The current study revealed that consistency of coreness over time within certain roles may be instrumental to team effectiveness. Large swings or fluctuations in coreness between players appeared to negatively impact team performance. Teams with more consistent trajectories within specific roles tended to perform better overall.

Lastly, the current work adds to the literature in that it provides new insights into how individual level performance impacts team effectiveness. Our results suggests that more centralized teams (that were dominated by a few players) tended to be both more successful at the team level, and to have more valuable players. In other words, more interdependence had a negative impact on the relative contributions of core players and tended to be detrimental to team effectiveness. This indicates that properly staffing core roles is of utmost importance to team success and that attempting to create a more “evenly” spread workload or even distribution of tasks may be detrimental to team outcomes when allowing the most capable team members to take on a dominant role may prove a better strategy.

**Implications for Practice**

The current research is relevant in applied settings because it utilizes a dynamic framework to understanding team processes. The current study has implications for organizational because the findings highlight the importance of standardizing roles on teams to enhance team effectiveness. In addition, the current work has important implications for selection, training, and performance appraisal because it highlights the importance of considering roles in selection and evaluation. Lastly, the current study impacts organizations because it
highlights the importance of aligning members of the strategic core such that the strongest human capital is applied to the organization’s strategy. I will discuss each of these implications next.

This kind of research could be beneficial to organizations seeking to implement a social network framework to both individual and team-level performance. While the current data dealt with sports teams, organizations could use email, interaction and/or performance data to inform a similar analysis. These methods provide a map for understanding of how actual interactions take place between employees. This approach could be utilized to understand how information flows within teams and how this impacts social processes (Klünder et al., 2016) or how interaction patterns differentially unfold between members of a team based on interactions with management (LMX; Sparrowe & Liden, 2005). The current work could help encourage more research into how interactions between organizational members impacts organizational outcomes at the group-level. Perhaps organizations can identify team roles that are central to team outcomes by examining information flow between workers using SNA. By analyzing the way core roles are performed and its impact on team level managers could identify organizational leaders and better support workers in these roles.

Analytical tools such as a profile analysis could be a useful tool for selection, training, and performance evaluation. For example, once a training has been implemented, it can be difficult to pinpoint how employee performance changes over time, especially with a small sample size in training groups. Using tools such as a profile analysis could help IO practitioners track changes to employee performance over time. This could aid in pinpointing performance dips at predictable intervals post-training which could be an indicator of when a refresher might be needed. Profile analysis could be a useful tool in determine the appropriate timing of training
interventions and refreshers and for identifying whether and how the performance of core team members impacts team effectiveness. If SNA and profile analyses are used in the aforementioned ways to alter trainings, these tools could also be used to track and evaluate performance. Additionally, if core roles on a team are identified through their influence on team performance, additional resources should be devoted to the development of selection procedures aimed at maximizing performance of employees in core team roles.

The current study bolstered our understanding that selecting highly skilled applicants for core team roles is vital to the success of any team. Interestingly, in the teams we observed, higher levels of team interaction seemed to detract from the performance outcomes of core players, and when highly skilled players were teamed with players who were more consistent and supportive this lent itself to the overall effectiveness of the team. It is unclear whether the same pattern would be observed in applied settings – this is highly dependent on the nature of the team in question. However, unitizing the same approach in an exploratory manner to understand how the skill level of employees in different team roles contributes to team success is a worthwhile undertaking. Hopefully the current study raises awareness of these methods and prompts additional applied research into this question.

**Limitations**

There are a number of limitations to the current study. The first involves the way in which data were collected which cannot allow for a full picture of interactive gameplay from an objective perspective. Moreover, while PIE score was useful in measuring performance, it too had limitation in what dimensions of performance were captured. Another limitation is that the current data did not measure psychological variables that may have contributed to the interactions that were observed. Additionally, more analyses are needed to fully understand how
player position impacts coreness and player and team-level performance. The current study took one of many possible approaches to understanding the impact of team level metrics on performance of top players and lastly additional analytical tools would have been helpful in further understanding how network metrics impacted performance but were time prohibitive. I will discuss each of these limitations next.

In recording passing interactions for each game across the 2016-2017 NBA season, only offensive team strategies were effectively captured. Because passes were recorded by observing the changing possession of the ball over the course of each game, only offensive passes and player actions were accounted for. Naturally, this renders defensive actions of the opponent team all but imperceptible. The effect of the defensive team’s actions on the passing network of the offense is no doubt impactful, but these factors escaped measurement for practical reasons. This methodology also leaves unanswered questions about players who potentially “set up” or facilitate skilled players in scoring points for the team but do so without gaining possession of the ball (e.g., by blocking defensive players). For example, in considering the 1990’s Chicago Bulls, Dennis Rodman was an effective blocker, essentially freeing up the court so that the celebrated Michael Jordan would find himself unfettered while landing picturesque field goal shot after field goal shot. Is it possible to track the effectiveness of unsung heroes like Rodman and quantify their contributions to team outcomes if they are not contributing points and impacting performance measures like PIE and eventually, team-level box scores? The current data captures only one perspective of these dynamic interactions (from the point-of-view of the ball handler), but many perspectives and variables are at play on the court.

In the current study I used PIE score as a proxy for player performance, but this score has limitations and cannot fully measuring performance because it only captures certain game
events. Players who are strong blockers or defenders may not be contributing to the box score of the game (or achieving a higher PIE score) but they are facilitating the team in other ways. Additionally, players that set up shots (pass to a player who assists to a scoring player) may have great vision on the court for strategy, but only the players who directly assist or make a scoring shot are counted in the PIE performance scores. PIE score is limited in what it can tell us, but provides useful in terms of separating each players contribution from the team performance score.

The current data were effective in capturing observable interactions and performance data based on sports statistics but did not effectively capture other variables that may have contributed to interaction patterns between team members. Research has shown that team members tend to interact with others that are more like themselves (Erdem & Ozen, 2003). It is plausible that members on a team trust certain player more than others, or that the amount of time spent on a team with another player creates a social bond that may have impacted player interactions. While roles are one important factor of study that was examined in the current work, there were myriad psychological variables that were not measured that surely impacted passing interactions and team performance.

In our analysis of mean coreness metrics based on player positions revealed meaningful differences, but it was unclear how this impacted team success. It would be interesting to study how other network metrics varied between the five positions and how this contributed to the performance of players in those positions. For instance, is there an optimal “constellation” of network metrics that contribute to higher performance for point guards? How is it different from the metrics that aid centers in carrying out their duties on the court? An additional study that
looks at different strategies used to fulfill each positions requirement could be a fruitful next step.

In analyzing the impact of team metrics on the PIE scores of the most valuable players the current approach was taken out of expediency, but other approaches could have proved viable or perhaps more suitable. The current approach was to correlate overall team metrics with metrics for the highest performing player. This could have been approached in other ways: by aggregating the PIE score of the top three players (or all players on the team) and correlating that with team-level metrics. While the approach taken provided some insights into how team-level metrics impact players PIE scores, this approach was somewhat over-simplified in its scope.

Lastly, a more rigorous analysis could have been used to further understand the network metrics derived for each team. Exponential Random Graph Modelling (ERGM) is an analysis that allows for inferences to be made about network structures by comparing the observed network patterns to statistical alternatives (Harris, 2013). This kind of analysis would have enabled more definitive statements about whether or not the interactive structures observed enhanced or inhibited team performance (Lusher et al., 2014). While this approach would have achieved a more comprehensive understanding of how team metrics unfolded, it was not undertaken due to time constraints.

**Future Research Directions**

This research adds to work on social network theory by incorporating dynamic interactive data and using it to predict player performance statistics. This research raised additional questions about how other factors (e.g., actions of the defensive team) impacted social network calculations. In addition, incorporating more information about team roles could have been helpful to the analysis and needs to be further studied. In addition, the current study only
scratched the surface with respect to the impact of individual-level performance on team level success. I will discuss each of these areas for future research next.

While using observable NBA data could be considered a strength of the current study (e.g., it consists of publicly observable interactions, is associated with accurate statistical metrics, consists of members in defined roles with performance statistics that are tracked on multiple levels) it is also a weakness. As mentioned in the limitations section, data collection allowed for the consideration of only certain actions of players who had possession of the basketball during game play. For ease of data collection this approach was practical. However, it is impossible to know how this approach impacted the data in aggregate (e.g., social network calculations). Perhaps future research will take all dynamics of court interaction into account when building theoretical models.

The findings of the current study suggests that coreness varied as a function of player position. It could be interesting to develop a theoretical model to explore the reason for this difference, and to delve deeper into the question of team roles more specifically. How does strong performance in particular team roles impact team success? Lastly, the results suggest that more centralized team networks are better for player-level performance, but perhaps this is detrimental to the team. The relationship between team and player level interactions needs to be further explored. It could be fruitful to examine the ways that players enact roles on different teams and how these methods contribute to team success.

A more sophisticated analytical approach could have helped understand how network metrics impacted player-level metrics from a process standpoint (e.g., by using an exponential random graph model approach). The ERGM approach quantifies observable team interactions that contribute to results (Harris, 2013; Kilduff & Brass, 2010). While the correlations,
ANOVA, profile analysis all facilitated a better understanding of how player interactions impacted team success, future work should focus on process models that help to unravel how these team and individual-level processes unfold over time.

**Conclusion**

The current study advanced our understanding of how the use of social network analysis and dynamic interactive data can be used to understand how individual performance impacts team effectiveness. The results indicated that coreness (i.e. centrality) on teams predicted player performance. In addition, the study revealed the importance of considering the impact of team roles in interpreting how individual-level outcomes impact team performance. The results revealed that player-level coreness varied as a function of team role. The ways in which individual level performance changes over time as a function of team membership was also investigated using profile plots. The findings indicated that teams with more consistent distributions of coreness tended to perform better, generally. Lastly, this research made it clear that individual interactions and team-level metrics have a recursive relationship. It was clear that teams with highly skilled players performed better when their interactions were more centralized, allowing for skilled players to dominate the team interactions. While individual metrics roll up into team-level processes, team level interactions can also influence the contributions of key players on a team.

Fruitful next steps would be to further isolate and explore how and why particular roles impact the coreness of players. It could be helpful to study how the same role varies from team to team, and how that impacts team effectiveness. Using SNA on different kinds of applied teams would add to the current body of research and help further unravel how individual level performance within specific roles impacts team outcomes. Lastly, more sophisticated analysis
like ERGM could help further our understanding of which patterns of interactions within teams are most impactful to performance


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https://stats.nba.com/players/advanced/?sort=GP&dir=-1


Appendix A

Mathematical Formulas for Calculating Social Network Metrics

Individual-level Metrics

1. Closeness Centrality: \( C_c(i) = \frac{n-1}{\sum_{j=1}^{n} d(i,j)} \)

2. Betweenness Centrality: \( C_B(i) = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \)

3. In-degree Centrality: \( C_D(i) = \frac{d(i)}{n-1} \)

4. Out-degree Centrality: \( C_D(i) = \frac{d(i)}{n-1} \)

Note. \( C = \) Centrality. \( i = \) node in question. \( n = \) number of nodes in network. \( j = \) all other nodes in the network. \( d = \) distance (in edges) from node to node.

Network-level Metrics

1. Density: \( \frac{\text{# actual relations}}{\text{possible relations}} \)

2. Centralization: \( C = \frac{\sum_{i}[c^* - c_i]}{\max \sum_{i}[c^* - c_i]} \)

3. Transitivity: \( \frac{\text{# of actual transitive triples}}{\text{possible transitive triples}} \)

4. Diameter: (count number of edges)

5. Distance: (average shortest path between all nodes)

6. Reciprocity (dyadic): \( \frac{\text{# reciprocated relations}}{\text{total # of relations}} \)
Figure 1. Manually coded passing sequences for the San Antonio Spurs (SAS) and Golden State Warriors (GSW) (left) and resulting edge list (right) for the SAS that shows passing relationships broken out into dyadic pairs. Adapted from Meyers & Gleason (2020).
Figure 2. An example of a sociomatrix (above) summarizing all passes between players during gameplay and the resulting passing network visualization generated from this data (below). Adapted from Meyers & Gleason (2020).
Figure 3. A social network configuration constructed using passing sequence data. Adapted from Meyers & Gleason (2020).
Figure 4 Atlanta Hawks composite coreness scores for four players over 25 games.
Figure 5. Broklyn Nets composite coreness scores for four players over 25 games.
Figure 6. Boston Celtics composite coreness scores for four players over 25 games.
Figure 7. Charlotte Hornets composite coreness scores for four players over 25 games.
Figure 8. Chicago Bulls composite coreness scores for four players over 25 games.
Figure 9. Cleveland Cavaliers composite coreness scores for four players over 25 games.
Figure 10. Dallas Mavericks composite coreness scores for four players over 25 games.
Figure 11. Denver Nuggets composite coreness scores for four players over 25 games.
Figure 12. Detroit Pistons composite coreness scores for four players over 25 games.
Figure 13. Golden State Warriors composite coreness scores for four players over 25 games.
Figure 14. Houston Rockets composite coreness scores for four players over 25 games.
Figure 15. Indiana Pacers composite coreness scores for four players over 25 games.
Figure 16. Los Angeles Clippers composite coreness scores for four players over 25 games.
Figure 17. Los Angeles Lakers composite coreness scores for four players over 25 games.
Figure 18. Memphis Grizzlies composite coreness scores for four players over 25 games.
Figure 19. Miami Heat composite coreness scores for four players over 25 games.
Figure 20. Milwaukee Bucks composite coreness scores for four players over 25 games.
Figure 21. Minnesota Timberwolves composite coreness scores for four players over 25 games.
Figure 22. New Orleans Pelicans composite coreness scores for four players over 25 games.
Figure 23. New York Knicks composite coreness scores for four players over 25 games.
Figure 24. Oklahoma City Thunder composite coreness scores for four players over 25 games.
Figure 25. Orlando Magic composite coreness scores for four players over 25 games.
Figure 26. Philadelphia 76ers composite coreness scores for four players over 25 games.
Figure 27. Phoenix Suns composite coreness scores for four players over 25 games.
Figure 28. Portland Trail Blazers composite coreness scores for four players over 25 games.
Figure 29. Sacramento Kings composite coreness scores for four players over 25 games.
Figure 30. San Antonio Spurs composite coreness scores for four players over 25 games.
Figure 31. Toronto Raptors composite coreness scores for four players over 25 games.
Figure 32. Utah Jazz composite coreness scores for four players over 25 games.
Figure 33. Washington Wizards coreness scores for four players over 25 games.