Understanding Teamwork Using Dynamic Network Models

Ashlyn Paige Lowe
DePaul University, ALOWE13@depaul.edu

Understanding Teamwork Using Dynamic Network Models

A Dissertation

Presented in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

By

Ashlyn Lowe

May 23, 2022

Department of Psychology

College of Science and Health

DePaul University

Chicago, Illinois

Dissertation Committee

Goran Kuljanin, Ph.D., Chairperson

Michael Braun, Ph.D.

Erich Dierdorff, Ph.D.

Kimberly Quinn, Ph.D.

Shelly Rauvola, Ph.D.

Acknowledgements

I would like to extend my sincere appreciation to my dissertation chair, Dr. Goran Kuljanin, for his support, guidance, and mentorship through the dissertation process and throughout my graduate school experience. I would also like to express my deepest gratitude to my parents, my family, and my friends for their continued support and encouragement. Lastly, I thank Becca Clancy and Tucker Jameson for consistently motivating me and providing support when I needed it most. Without all of you, I would not be where I am or who I am today.

Biography

The author was born in Milford, MI on October 18, 1994. She graduated from Milford High School in Highland, MI. She received her Bachelor of Science degree in Psychology from Michigan State University in June of 2016, and her Master of Arts degree in Industrial-Organizational Psychology from DePaul University in May of 2019.

Table of Contents

List of Tables

List of Figures

Abstract

Studying team processes is critical to understanding how teams work to achieve team outcomes. To effectively study team processes, behavioral activities team members enact must be measured with sufficient granularity and intensity. Analyzing the detailed mechanics of team processes requires employing analytical methods sensitive to modeling the series of actions and interactions of team members as they execute taskwork and teamwork over time. Current empirical investigation of team processes lags with respect to intricately measuring and assessing team processes over time. Using dynamic network models, this dissertation sought to understand the behaviors responsible for interaction patterns amongst team members, how those interaction patterns and structures relate to team member behavior, and how interactive team processes relate to team outcomes. Specifically, this dissertation utilized interaction-level data from the National Basketball Association (NBA) and applied three dynamic network models to the data: Separable Temporal Exponential Random Graph Modeling (STERGM), Stochastic Actor-Oriented Modeling (SAOM), and Relational Event Modeling (REM). The purpose of this dissertation is to provide a descriptive foundation for future studies using theories of time to study team phenomena and to demonstrate the utility of dynamic network models. This dissertation details the theoretical foundations of team processes and network analysis, the temporal extensions of traditional network analyses, the utility and applicability of dynamic network models (STERGM, SAOM and REM) using NBA data, and shows insights these methods provide for studying team processes. Results of this dissertation showed reciprocity to be the strongest passing pattern amongst NBA teams, followed by transitive passing patterns. Specifically, NBA players in the 2016-2017 season frequently formed mutual (between two players) and transitive (between three players) passing relations. Player position and scoring behavior were not found to influence passing patterns, nor was home versus away status. Forming mutual and transitive ties related to team wins based on STERGM analyses but similar passing patterns were not found to predict wins with REM analyses, reinforcing methodological and analytical differences in these dynamic network methods. This dissertation discusses the applicability, utility, and implications of applying these dynamic network models to studying team processes and provides practical information about how these methods can be used to inform future research and practice on team dynamics.

Keywords: teams, team process, network analysis, dynamic, process theory

Understanding Teamwork Using Dynamic Network Models

Team processes, or the interdependent actions team members take that convert inputs to outputs for the sake of accomplishing tasks and shared goals, are integral for studying teams (Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). Team processes include coordinating work, communicating with team members, and assessing progress towards team goals. Team processes explain how teams complete their work, making intervening on team processes critical for increasing the effectiveness of teamwork (McGrath, 1987; Braun, Kuljanin, Grand, Kozlowski & Chao, 2022). Organizational researchers typically study team processes within Hackman's (1987) Input-Process-Outcome (I-P-O) model of team effectiveness, which assesses how inputs (factors that enable or inhibit team member interactions) produce team outcomes via mediating processes. However, many of these examinations confine team processes to aggregate, coarse-grained and static mediating mechanisms which fail to capture how processes change over time (Ilgen, Hollenbeck, Johnson, & Jundt, 2005).

Studying team processes is critical to understanding how teams operate to achieve effective team outcomes. The study of team processes requires identifying what team members do to complete tasks (i.e., taskwork) and how team members collaborate with one another (i.e., teamwork) to execute taskwork. Thus, the interaction of taskwork and teamwork is what enables teams to convert inputs to outcomes through cognitive, verbal, and behavioral activities (Marks, Mathieu, & Zaccaro, 2001). Research to date links numerous team processes, such as information sharing (Hinsz, Tindale, & Vollrath, 1997; Mesmer-Magnus & DeChurch, 2009), intragroup conflict (De Wit, Greer, & Jehn, 2012), trust formation (Costa, Roe, & Taillieu, 2001; Jarvenpaa, Knoll, & Leidner, 1998), and the development of psychological safety (Edmondson, 1999) to team outcomes (e.g., team performance, team member satisfaction, team cohesion, team potency; LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). Despite the importance of studying team processes, the teams literature is limited with respect to evaluating team processes in the two central empirical phases of research: measurement and analysis.

To understand the mechanics of team processes, researchers and practitioners should seek to measure behavior with sufficient granularity and intensity of the behavioral activities team members enact with respect to taskwork and teamwork within performance episodes. A traditional approach to studying team processes involves using surveys taken by team members or observations of team member activities to cross-sectionally measure the perceived effectiveness of aggregate team behavior, such as communication, coordination, collaboration, leadership, or interpersonal support. This research approach misses two key aspects of team processes. First, this approach misses the actual behavioral granularity of taskwork and teamwork that team members execute to accomplish team objectives. Second, this approach misses what team members do *during* performance episodes. Instead, measurement should focus on intensively recording the behavioral actions and interactions of team members as they work to accomplish team objectives. This approach more directly speaks to what leads to the emergence of team outcomes, such as team cohesion, satisfaction, and performance.

To analyze the mechanics of team processes, researchers must employ analytical methods sensitive to modeling the stream of actions and interactions enacted by team members as they execute taskwork and teamwork during performance episodes. The commonly applied analytical approaches employed in psychology to study behavior over time generally capture trends and differences in trends (Dishop, Braun, Kuljanin, & DeShon, 2020). However, these methods cannot capture the patterns and sequences of team member actions and interactions during performance episodes. Instead, dynamic network models offer the possibility of modeling the patterns and sequencing of actions and interactions inherent in taskwork and teamwork. Dynamic network models allow for an examination of how networks change over time by considering how a network of interest can be explained by the interdependencies of individuals in a network (Liefeld & Crammer, 2015; Snijders, van de Bunt, & Steglich, 2010). These models consider the evolution of behavioral patterns rather than focusing on higher-order phenomena (Schecter, Pilny, Leung, Poole, & Contractor, 2017).

The purpose of this dissertation is to provide a descriptive foundation for future studies using theories of time to study team phenomena and to demonstrate the utility of dynamic network models. To show how these dynamic network models can be applied to studying team processes, this dissertation first describes the study of team processes in the literature and limitations of the current stream of research. It then details three key dynamic network models (Temporal Exponential Random Graph Modeling, Stochastic Actor-Oriented Modeling, and Relational Event Modeling) that can address current limitations. Throughout this dissertation, these dynamic network models are used to address one overarching question regarding teams: how do team members collaborate to actually perform their work?

Team Processes

A team is defined as a group of interdependent individuals working to achieve shared goals (Humphrey & Aime, 2014). The key feature of this definition that distinguishes teams from groups is *interdependence* (Humphrey & Aime, 2014). Interdependence within teams requires a focus on how team members work together and interact with one another to enhance team outcomes over time. These interactions constitute a key aspect of team processes (Burke, Stagl, Salas, Pierce, & Kendall, 2006), yet current investigations of team processes still rely on factor theories (i.e., focusing on a narrow set of factors) rather than process theories (i.e., focusing on actors and their actions) for studying team process (Braun et al., 2022).

Traditional Frameworks for Studying Teams

Team processes are defined as team members' interdependent actions aimed at achieving shared goals that convert team member inputs to relevant team outcomes via cognitive, verbal, affective, behavioral, and social activities (Marks et al., 2001). Team processes are traditionally studied using Hackman's (1987) model of interaction processes, which is based on McGrath's (1964) Input-Process-Output (I-P-O) model. Team inputs are antecedents that enable or constrain how team members interact and include individual team member characteristics, team-level factors, and organizational and contextual factors (Mathieu, Maynard, Rapp, & Gilson 2008; McGrath, 1964). Team outcomes are less specified as they are context specific and include both team behaviors (e.g., performance) and team member affective variables (Hackman, 1987). Team processes, such as collaboration, communication, and learning, result from interactive cognitive, affective and behavioral activities by team members and serve to link team inputs to team outcomes (Marks et al., 2001). While the I-P-O model is a useful starting point for studying team processes, its conceptualization has resulted in a primary focus on aggregated causal mechanisms between inputs and outcomes rather than studying the finer-grained components of processes underlying those causal mechanisms (Leenders, Contractor, & DeChurch, 2016).

To advance research on team processes, Marks and colleagues (2001) introduced a taxonomy of team processes. This taxonomy highlights the need to incorporate the notion of time into models of team processes and highlights how teamwork processes (i.e., *how* teams do their work) enable the necessary taskwork (i.e., *what* teams do) to achieve shared goals (Marks et al., 2001). The taxonomy is a recurring-phase model such that there is a sequential, temporal aspect of coordinating inputs, processes, and outcomes in which outcomes from one I-P-O episode become the inputs to a subsequent I-P-O episode. Thus, the taxonomy defines processes as how teams interact throughout multiepisodic goal attainment (Marks et al., 2001).

This framework posits teams enact a series of processes throughout their lifecycle, including transition processes, action processes and interpersonal processes (Marks et al., 2001). Transition processes are those in which team members focus on evaluation and planning activities of team behaviors to monitor progress towards team goals (e.g., formulating team strategy, specifying desired goals). Action processes are those in which team members are engaged in behaviors that directly contribute to the accomplishment of goals (e.g., monitoring progress towards goals, coordinating interdependent actions; Marks et al., 2001). Interpersonal processes serve to manage issues that may inhibit goal accomplishment in teams (e.g., conflict, motivation, affect; Marks et al., 2001). This framework highlights the need to identify critical performance episodes over time to understand what and *when* certain team processes become imperative for goal accomplishment, serving as a call to action for researchers studying team processes to consider how inputs lead to outcomes *over time*.

The taxonomy of team processes led researchers to reevaluate the utility of traditional I-P-O models in characterizing teams. Ilgen and colleagues (2005) point to three key limitations in using I-P-O models: (1) the “processes” conceptualized in the I-P-O model are actually a composite of both process and cognitive or affective states; (2) the single-cycle linear nature of the I-P-O model fails to capture potential feedback loops in team processes; (3) the I-P-O model suggests a linear trajectory from inputs to outputs, failing to account for the interactions between multiple processes, inputs and processes, and inputs, processes, and emergent states (or the dynamic properties of teams that change as a function of team context, inputs, processes and outcomes; Ilgen et al., 2005). To account for these limitations, Ilgen and colleagues (2005) proposed the Input Mediator Output Input framework (IMOI), which (1) replaced the original "P" (processes) with an "M" (mediators) to encompass a broader range of mechanisms that may convert inputs to outcomes, (2) added a second "I" (inputs) at the end of the model to represent the cyclical nature of team processes, and (3) removed the hyphen between letters to signify non-linear causal linkages across inputs, mediators, and outputs. This framework further highlighted the need to examine how and what teams do as they perform their work.

When examining teamwork, it is important to distinguish team processes from team emergent states. Team processes consist of team member independent and interdependent behavioral, affective, cognitive, and social *activities* that produce various emergent states (Marks et al., 2001). Team processes provide insight into how team members plan their work, the actions they take to complete their work, and how they manage interpersonal phenomena that arise within teams (Marks et al., 2001). Emergent states are dynamic properties of teams that change based on team context, inputs, processes, and outcomes (Mathieu et al., 2017). Examples of emergent states include team cohesion (Gully, Devine, & Whitney, 1995), efficacy (Gully, Devine, Incalcaterra, Joshi & Beaubien, 2002), and cognition (Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016; Mathieu et al., 2008). While emergent states focus on the dynamic characteristics of a team that change over time, they do not actually describe the actions team members take that result in these emergent states. Distinguishing team processes from emergent states suggests a need for more nuanced study of the underlying mechanisms of observed psychological phenomena.

Limitations of Current Empirical Investigations of Teamwork

While the I-P-O and IMOI frameworks facilitate consideration of how to study teamwork, empirical research continues to lag with respect to intricately measuring and assessing team processes over time. Leenders and colleagues (2016) highlight four key limitations to current empirical investigations of teamwork. A first limitation is measuring team processes as an aggregated summary index. For example, research finds information sharing enhances team outcomes (Mesmer-Magnus & DeChurch, 2009). However, the statement of this relationship minimally does not inform (1) how team members actually share information (e.g., do team members share information only during meetings or intermittently throughout their project work? Do team members share information to the same degree?) nor (2) the effective boundaries of information sharing to impact team outcomes (e.g., is information sharing endlessly positive for team outcomes?).

A second limitation of current empirical investigations of teamwork is assuming homogeneity of interactions between all team members (Leenders et al., 2016). Interactions are typically aggregated across the team and assume local interactions (e.g., dyadic) are equivalent to global interactions (e.g., team; Leenders et al., 2016). Aggregating interactions loses critical information, such as identifying how each team member contributes to ongoing teamwork. Together, aggregating team processes and interactions does not provide a detailed examination of teamwork. Instead, data collection focused on granular activities and interactions offers such an examination.

A third limitation of current empirical investigations of teamwork is relying on underdeveloped theories of teamwork with respect to time scales (Leenders et al., 2016; Mitchell & James, 2001). Teams may change how they enact their team processes over numerous performance episodes. Empirical studies measuring teamwork only for a few, poorly specified performance episodes more than likely miss important insights into how team members may alter how they perform their work. This requires measuring what team members do over several performance episodes, or, at the very least, identifying what performance episodes to measure to sufficiently capture team process dynamics.

A fourth limitation of current empirical investigations of teamwork is assuming repeated measurements capture team processes more granularly. Repeated measurements of aggregated team processes and interactions may provide some insights into aggregated contemporaneous and lagged effects, but it still does not provide granular information on how team members accomplish their work. Gathering several measurements of aggregated team information sharing does not detail *how* team members share information with one another. This points to a need for data collection focused on measuring what happens *within* performance episodes and not just measuring aggregations of team processes and interactions over several performance episodes.

Overcoming Limitations: A Focus on Emergence

Emergence of team states occurs as a process by which individual characteristics at a lower level create higher-level properties of a team through individual characteristics and dynamic decisions, thoughts, feelings, actions, and interactions (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). Emergent phenomena are multilevel, process-oriented, and take time to manifest at a higher level (Kozlowski et al., 2013; Kozlowski & Klein, 2000). Due to the multilevel, process-oriented nature of taskwork and teamwork, researchers and practitioners benefit from considering emergence when studying teams. Indeed, past research has generally studied team phenomena in a static, aggregated form. Researchers typically use factor theories when studying teams, which assess a narrow set of factors to test specific hypotheses (Braun et al., 2022). Factor theories tend to overlook broader organizational context as they seek to explain covariance relationships amongst a set of factors. Specifically, they assess how changes in one variable correlate with changes in another variable, which does not consider the underlying processes that contribute to the observed relationship over time (Braun et al., 2022). As a result, this limits team process interventions to broad, simplistic advice such as an increase in information sharing improves team outcomes. Alternatively, focusing on the emergence of team phenomena (e.g., team performance) provides an opportunity for team process interventions focused on what team members can more specifically do and how they should do it to improve team outcomes (see Grand et al., 2016).

Ideally, to capture an emergence process, researchers would assess teams at preformation, study a team's context, and examine the team long enough to observe the dynamic nature of a phenomenon of interest (Kozlowski et al., 2013). The goal would be to capture both team processes (i.e., what teams are doing and how they are doing it) and team structures (i.e., who does what) that enable or constrain those processes (Kozlowski et al., 2013). While organizational systems theorists have noted the need to study both process and context collectively (Kozlowski et al., 2016), this approach in teams research is often neglected. To do this well requires intensive, longitudinal examinations that capture granular team interactions (Kozlowski et al., 2013).

When studying team phenomena, empirical researchers have typically taken an attribute-based approach in which they examine the influence of aggregated team member attributes on aggregated team processes and outcomes (Bell, Villado, Lukasik, Belau, & Briggs, 2011; Borgatti & Ofem, 2010). However, this lens alone does not sufficiently capture intrateam relational dynamics between team members, such as how team members sharing a similar attribute might differentially interact with one another relative to the team, and how this impacts team outcomes over time. To understand intrateam relational dynamics, teams researchers can use a network analysis approach to study how team members collectively accomplish team tasks by adopting an interactionist perspective (Brass, 2011). This perspective incorporates the intersection of individual attributes and their context in creating a network structure for a team (Brass, 2011), which researchers consider as a key pillar of studying emergence in teams

(Kozlowski et al., 2016). While most research on team networks has been conducted on static networks (i.e., using a single time point), there are methods for studying relational networks over time that better unveil team processes (Leenders et al., 2016).

A Network Approach to Studying Team Processes

Network analyses study relations among actors to examine underlying social structures that inhibit or foster team interactions (Lusher, Robins, & Kremer, 2010). While traditional network analyses begin to capture complex interrelations within teams, they remain limited due to their static nature. Alternatively, researchers can use dynamic network models which treat time as integral in modeling team phenomena. These approaches move researchers closer to analyzing finer-grained team data to better test theories of teams and advance teams research beyond static examinations.

Social Network Analysis

Social science research traditionally adopts an attribute-based approach in which individuals are the primary focus. An alternative approach is to study networks in which the primary focus is on the relationships between actors and how the intersection of relationships enables or constrains behavior within the context of their environment (Borgatti & Ofem, 2010). There are two key realms of inquiry for studying networks: *theory of networks* and *network theory*. A *theory of networks* approach focuses on examining the antecedents of network variables (i.e., studying network evolution whereby network processes result in network structures). A *network theory* approach focuses on examining the consequences of network variables (i.e., how a system comes together determines the behavior and outcomes of a system; Borgatti & Halgin, 2011;

Borgatti & Ofem, 2010). Naturally, studying networks through both theoretical lenses better provides a complete picture of network phenomena (Borgatti & Halgin, 2011).

The basic analytical approach for networks composed of individuals is known as social network analysis (SNA) in which the relationships among actors and social entities are analyzed to examine the social structures that these relations produce (Lusher et al., 2010). Viewing organizations as networks conceptualizes network structures as patterns of member relationships (Warner, Bowers, & Dixon, 2012). This perspective also views a network's environment as either constraining or enabling individual behavior (Warner et al., 2012). *Figure 1* shows the basic network terminology used in network analysis. The network itself consists of a set of actors, or nodes, which can be individuals, teams, organizations, or any entity that is linked to another entity (Borgatti & Ofem, 2010). Additionally, the network includes edges (ties), or the set of relations between entities in the network (Borgatti & Ofem, 2010). An edge connecting two actors is called a dyad and represents a relationship or some other type of connection between two actors. SNA facilitates an understanding of who comprises a network (i.e., who are the actors), what actors are connected, network sub-structures (e.g., reciprocity – reciprocating a connection; triads – a grouping of three actors; clusters – groups of actors within a network; cores – a central group of actors within a network), and the boundary conditions of a network (Lusher et al., 2010). SNA may account for the structural nature of teams while also considering attributes of team members, making it a viable method for exploring complex relations within teams (Lusher et al., 2010). It complements traditional multilevel psychological research by focusing on relations beyond individual and aggregated team attributes to examine multilevel interdependencies of individuals within teams.

Figure 1

Basic Network Terminology

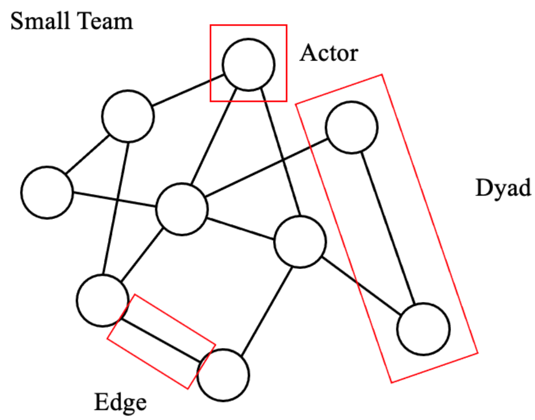


Figure 1. Example network which includes actors (i.e., individuals), edges (i.e., the linkages between two actors), and dyads (i.e., a pairing of two actors).

A traditional SNA approach, however, is limited to a static examination of a single network snapshot. While network scholars agree structural relations within networks continually change amongst social entities (Knoke & Yang, 2008), a traditional SNA approach does little to capture these processes in action. The inability of SNA to capture the sequences of network changes or actions by actors limits the ability of researchers to understand ongoing processes and identify areas of intervention for process improvement (Ployhart & Vandenberg, 2010). Although SNA enables an examination of complex relations between individuals rather than simply aggregating individual relations to represent the whole team, capturing team processes requires the collection of longitudinal data to assess how patterns of relations form and change over time.

Dynamic Network Models

Researchers have utilized different analytical approaches to model networks observed over multiple time periods. One approach uses multilevel regression (Lubbers, Molina, Lerner, Brandes, Ávila, & McCarty, 2010). While traditional regression analysis on network data violates assumptions of observational independence based on the relational dependence within networks (Snijders, 1996), nesting network observations controls for this violation (Lubbers et al., 2010). Specifically, the relationships of actors in a network are nested within the actors themselves which allows researchers to decompose the variance of the criterion variable at different levels (Lubbers et al., 2010). However, there are additional network analysis methods designed specifically to handle violations of independent observations and capture the dynamic nature of networks over time.

The methods designed to capture longitudinal network data will be referred to as dynamic network models. Three primary dynamic network models are used in this dissertation: Separable Temporal Exponential Random Graph Modeling (STERGM; Morris, Krivitsky, Handcock, Butts, Hunter, Goodreau, & Bender-deMoll, 2019), Stochastic Actor-Oriented Modeling (SAOM; Snijders, 1996; Snijders, Van de Bunt, & Steglich, 2010; Snijders, 2016), and Relational Event Modeling (REM; Leenders et al., 2016; Schector & Contractor, 2017). These three models extend static network analyses by requiring specification of time-based network dependencies, facilitating the study of team processes.

Figure 2 shows a tree diagram summarizing the theoretical origin for each model used in this dissertation. The original random graph models are the Erdös-Rényi-Gilbert random graph models, which sparked the field of random graph theory (Erdös & Rényi, 1959; Gilbert, 1959; Goldenberg, Zheng, Fienberg, & Airoldi, 2010). Erdös & Rényi (1959) posited a one-parameter model in which all graphs on a fixed set of actors with a fixed number of edges are equally likely to occur and assessed the properties of the model as the number of edges increases. Gilbert (1959) posited a two-parameter model in which all edges have a fixed probability of being present or absent, independently of other edges (Goldenberg et al., 2010). Although initial descriptions are defined in static terms, both models provide a path towards examining dynamic network patterns. Holland & Leinhardt (1981) extended the Erdös-Rényi-Gilbert random graph models to an expanded p1 model which includes differential attraction for actors (i.e., measuring popularity) and reciprocity of interactions. The p1 model takes a log-linear form, enabling efficient computation of maximum likelihood estimates (MLE) and allowing for various generalizations to multidimensional network structures (Goldenberg et al., 2010). ERGM, originated by Frank and Strauss (1986) soon followed p1 models, which distinguishes between random and predictable patterns present in a network. ERGM uses a single time point to assess the inclusion of network features within a regression-like framework (Fritz, Lebacher, & Kauermann, 2019).

To move beyond static examinations, Markov-chain based models were introduced. A Markov-chain model is a stochastic model that describes the sequence of possible events in which the probability of an event depends on the state attained in the previous event (Frank & Strauss, 1986). To utilize discrete longitudinal data, STERGM and SAOM were introduced. STERGM is a temporal extension of ERGM that separately models relation formation and dissolution (Krivitsky & Handcock, 2014). STERGM

Figure 2

Theoretical Origin of Dynamic Network Models

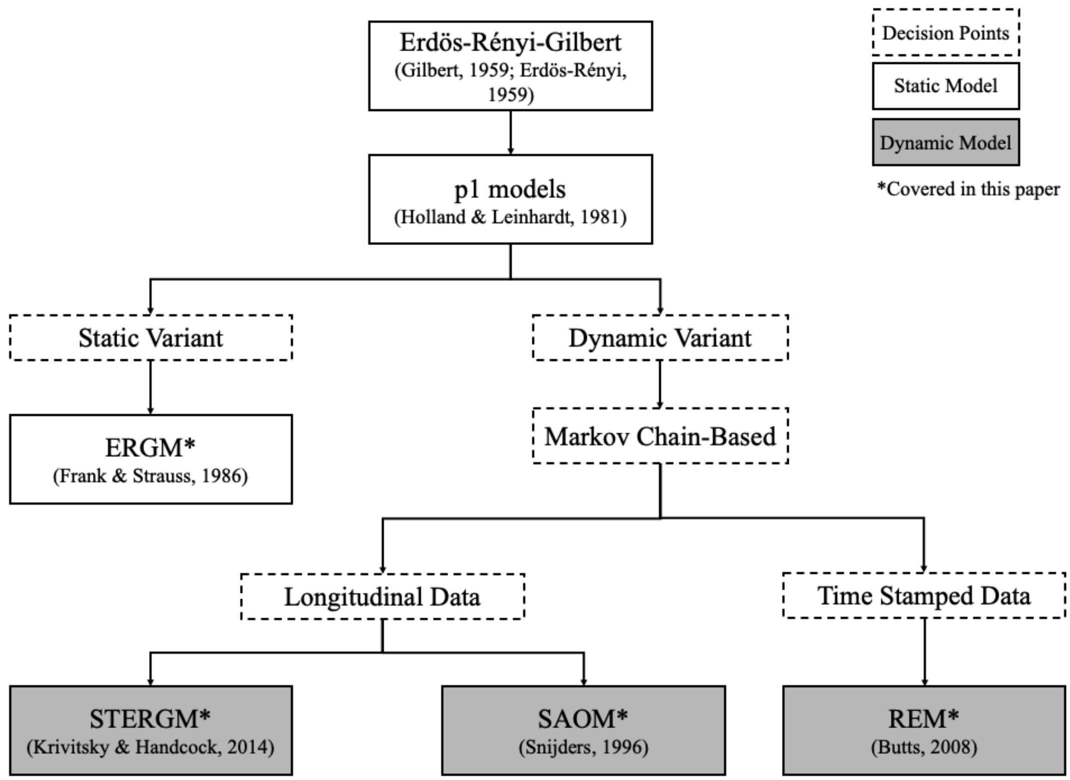


Figure 2. Adapted from Fritz et al., (2019). Tree diagram of theoretical origin for dynamic network models used in this paper. ERGM = Exponential Random Graph Model; STERGM = Separable Temporal Exponential Random Graph Model; SAOM = Stochastic Actor-Oriented Model; REM = Relational Event Model.

distinguishes between random and predictable patterns present in a network based on all observed networks up to a given time point. SAOM asserts that change stems from individual decisions, making SAOM an actor-oriented model that assesses the propensity for actors to alter relations based on their surrounding network structure from an individual perspective (Block, Koskinen, Hollway, Steglich, & Stadtfeld, 2018). To utilize longitudinal continuous data, REM was introduced. REM assesses individually time-stamped interactions between any two entities, making it the most fine-grained examination of interaction processes (Schecter et al., 2018). Each network analysis method provides a unique examination of how group phenomena occur.

Before discussing the dynamic network models used in this dissertation in detail, *Figure 3* presents a conceptual map to highlight terminology used in these models and illustrate differences and similarities between these models. The figure includes the following concepts:

(A) *sending actors*, representing senders of an action,

(B) *receiving actors*, representing recipients of an action,

(C) *actor attributes*, representing individual attributes such as gender, personality, job role, etc.,

(D) *network structure*, representing connections between actors,

(E) *external factors*, representing changes in the network environment,

(F) *time*, representing a network observed over multiple time periods, and

(G) *event history*, representing a sequence of actions.

Figure 3 shows the exchange pattern of a single team. Team members take one of two values on an individual characteristic attribute, represented by triangular or circular shapes. The actors are presented with a time-bound deadline for their work, representing an external factor that serves to impact how actors interact. At Time 1, Actor 1 and Actor 7 decide to send outgoing edges to Actor 3 and Actor 10, respectively; Actor 8 decides to maintain its edge with Actor 6; Actor 4 decides to dissolve its edge with Actor 2. Time 2 presents actors with similar decisions. To represent the formation of an event history, Actor 4 chooses one of a set of options between Time 1 and Time 2. In particular, Actor 4 has three options: (1) to create a new edge to another actor, denoted by a solid black line;

(2) to maintain its edge to Actor 2, denoted by a solid gray line; (3) or to dissolve its edge to Actor 2, denoted by a dashed black line. Time 2 shows Actor 4's decision to send a new edge to Actor 3. The concepts presented in *Figure 3* serve as a foundation for describing and comparing these models to each other.

Exponential Random Graph Models

To better understand dynamic network models, one must first understand the static network analytic method that serves as a basis for STERGM. Exponential Random Graph Models (ERGM) predict the occurrence of network relations, or connections between individuals (Lusher et al., 2014). ERGM enables analysts to simultaneously model individual variables (e.g., actor attributes) and network structure variables (e.g., reciprocal relations between two individuals; Lusher et al., 2014). These models are designed to distinguish between predictable versus random patterns present in a network (Chrobot-Mason, Gerbasi, & Cullen-Lester, 2016; Lusher et al., 2014). As ERGM enables hypothesis testing of various explanations for the occurrence of structural network patterns, it is used for examining interdependent psychological phenomena (Lusher et al., 2014).

ERGM Theoretical Foundation. Relational data are inherently interdependent as a relation that occurs between two individuals relies on both entities. Traditional psychological research methods assume independence of observations, thus resulting in disconnection between theory and research method for relational data (Lusher et al., 2014). ERGM was originally introduced by Frank and Strauss (1986) to address the inherent dependence of relational phenomena. ERGM treats each network connection as a random variable, modeling network edges explicitly to assess the collection of local

Figure 3

Conceptual Map for Dynamic Network Models

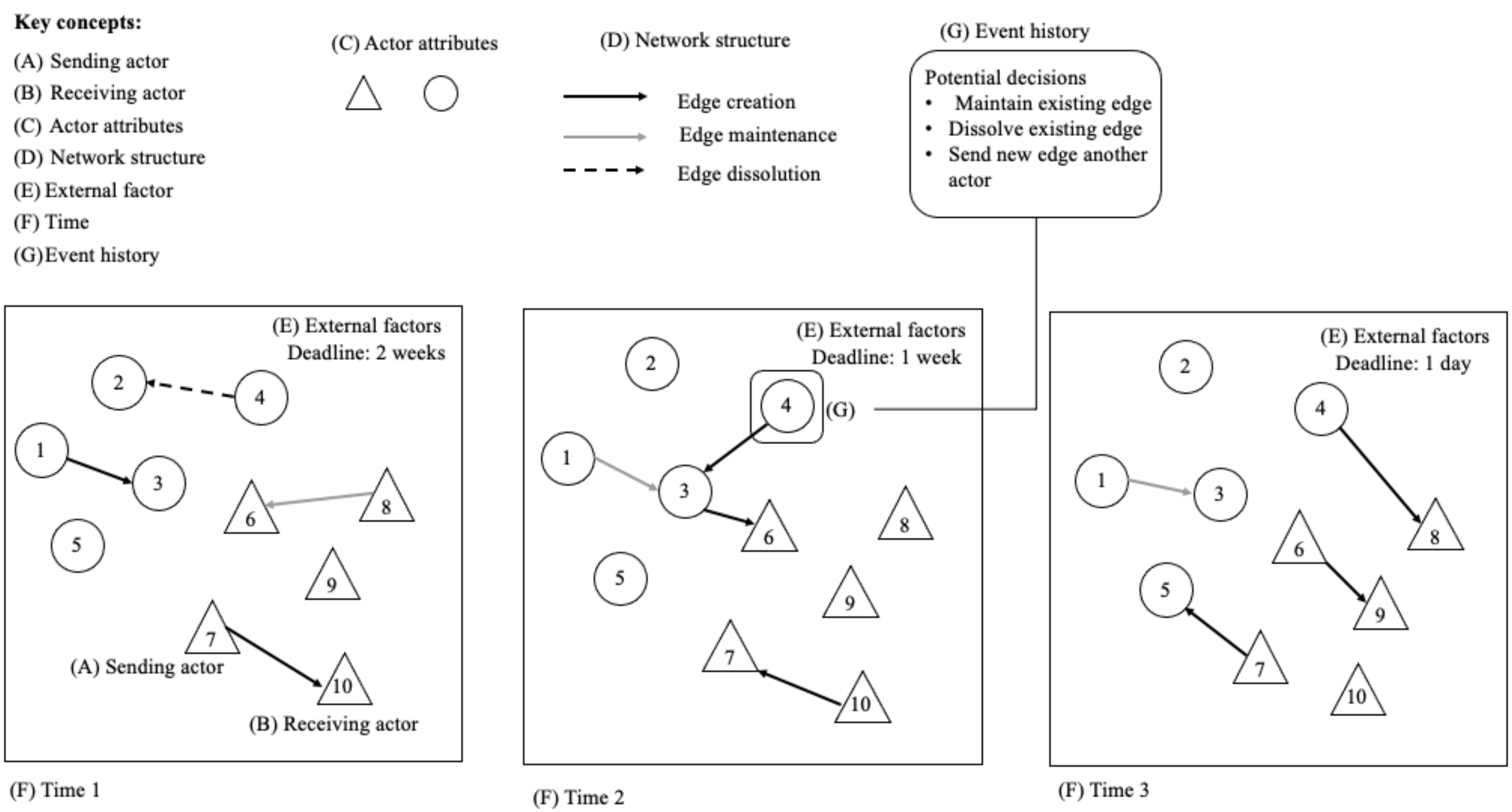


Figure 3. Figure 3 represents the communication between two teams over three time points and includes seven key concepts for dynamic network models (sending actors, receiving actors, actor attributes, network structure, external factors, time, and event history).

relational patterns to form global network structures (Lusher et al., 2014). ERGM addresses the disconnection between theory and method by assessing complex, interdependent social structures through an explicit assumption of interdependent observations (Lusher et al., 2010).

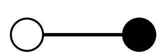
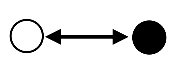
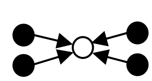
The methodological core of ERGM is an edge embedded within social structures, making the edge level its unit of analysis (Block et al., 2018). The social structures that dictate edge formation can be both endogenous network processes and processes related to actor attributes (Lusher et al., 2014). Endogenous network processes are purely structural network effects that suggest how ties form is due to the presence or absence of other ties. Ties may also form due to actor attributes, underscoring the cross-section of relations and individual attributes (Lusher et al., 2014). Focusing purely on structure or attributes is likely insufficient in explaining phenomena of interest, making ERGM suitable for examining the intersection of network structure and individual attributes in studying psychological phenomena.

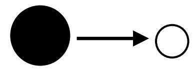
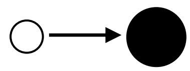
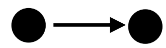
ERGM specification assesses higher-order social phenomena by including both social structures and individual attributes to examine network properties. By assessing the structural properties that underly network configurations, ERGM works as a pattern-recognition device to predict *why* social relations occur, thus, assessing the consequences of dynamic processes (Lusher et al., 2014). Moreover, ERGM allows for modeling tie variables as both a criterion and a predictor, enabling assessment of feedback loops between network phenomena that are critical in modeling complex interdependencies among network tie variables (Lusher et al., 2010). ERGM requires researchers to consider the multiple, intersecting explanations for phenomena of interest, enabling a broader range of theoretical consideration for constructs, making ERGM a viable method for assessing the social mechanisms responsible for relations within a network (Lusher et al., 2014).

ERGM Mathematical Foundation. The primary goal of ERGM is to model the probability of an edge forming between two actors in a network as a function of network effects and actor attributes. *Table 1* shows example network effects that can be modeled using ERGM, organized by whether the effects are structural or actor-related (derived from Lusher et al., 2014). More specifically, structural effects suggest social processes contribute to edge formation whereas actor-related effects suggest actor attributes contribute to edge formation. For example, ERGM can model the likelihood of an edge forming (a) generally in a given network (*arc*), (b) if an actor will reciprocate an edge (*mutual*), (c) based on an actor's popularity (*popularity spread*), (d) based on an attribute of a *sender*, (e) based on an attribute of a *recipient*, or (e) based on a shared attribute between two actors (*homophily*; Lusher et al, 2014).

Table 1

Sample Network Effects Modeled in ERGM

Effect Type	Parameter	Visual	Explanation
Structural	Arc (outgoing edge)		Actor sending information determines edge formation
	Mutual (reciprocity)		Reciprocity of actors determines edge formation
	Popularity spread		Popularity of an actor determines edge formation

Actor-Related	Sender		Sender attribute determines outgoing edge
	Recipient		Recipient attribute determines incoming edge
	Homophily		Shared sender and recipient attribute determine outgoing edge

Note. Adapted from Lusher at al. (2014).

Using the foundational conceptual map for dynamic network models, *Figure 4* describes the key terms modeled in ERGM. ERGM examines static networks and does not include (F) time or (G) event history. For simplicity of this foundational example, *Figure 4* does not include (C) actor attributes or (E) external factors. This conceptual foundation includes (A) a sending actor, (B) a receiving actor, and (D) an action taken by the actors that produce the network structure, with solid lines representing existing edges in the network.

Figure 4

Conceptual Foundation for ERGM

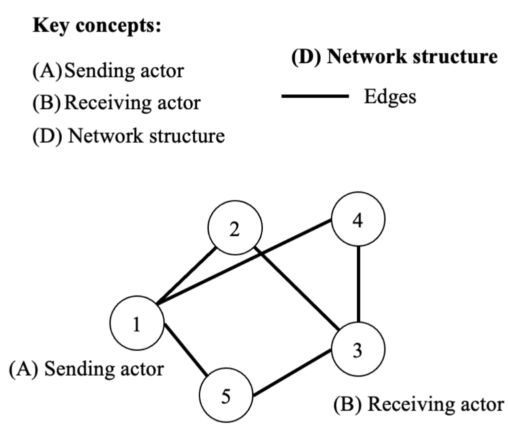


Figure 4. Figure 4 presents a conceptual foundation for ERGM, including a sending actor (A), a receiving actor (B) and network structure (D), indicated by a solid line.

General ERGMs take the following form

$$P(X = x) = \frac{exp\{\theta^t g(y,x)\}}{\sum_{y\prime \in y} exp\{\theta^t g(y\prime,x)\}} \quad (1)$$

where y ∈ y represents a random graph, X is a vector of attributes, θ^t represents the transpose (t) of the vector of model parameters (θ), and g(y, x) represents a function which returns a vector of sufficient statistics. The numerator represents any network y as a function of statistics provided by g(y, x) in the network y on parameters provided by θ^t, and the denominator sums all $\theta^t g(y, x)$ over all permutated network configurations with the same number of actors to assess the probability of any network y occurring based on these parameters (Leifeld, Cranmer, & Desmarais, 2018; Robins, Snijders, Wang, Handcock, & Pattison, 2007). Maximum Likelihood Estimation (MLE) uses observed data to estimate ERGM model coefficients. Once the model is estimated, then networks can be simulated to represent the probability distribution of networks of the same size. *Figure 5* shows an example observed network and six simulated networks. The simulated networks may be compared to the observed network to assess how well the proposed model fits the data.

The ERGM model equation can be reformulated to calculate the conditional log-odds of a single tie between two actors. This reformulation results in the following expression:

$$logit(Pr(Y_{ij} = 1 \mid Y^C)) = \theta' \Delta\, (g(y))_{ij} \quad (2)$$

where Y_{ij} represents a random variable indicating a possible tie between a pair of actors (i, j); Y^C represents the network of ties excluding actors i and j; θ represents model

Figure 5

Example of ERGM Simulated Networks

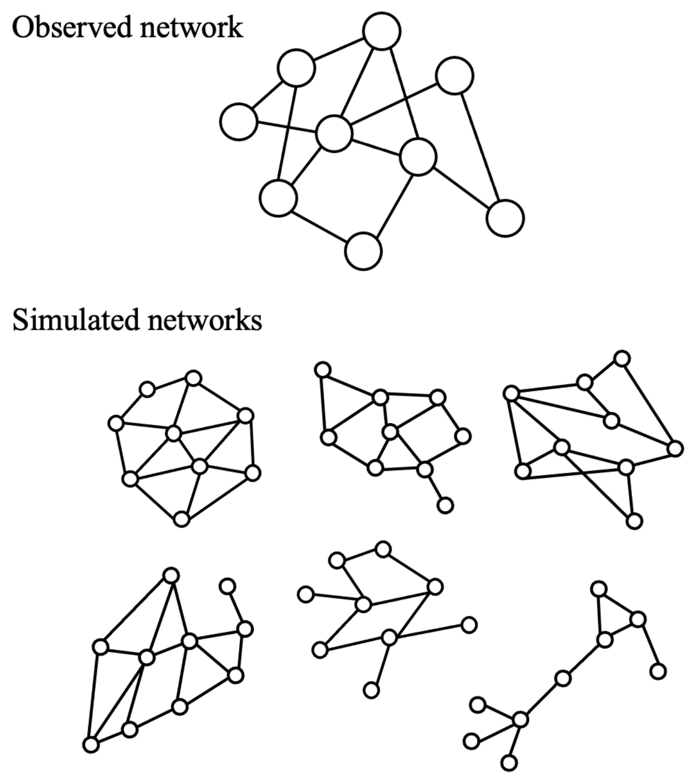


Figure 5. ERGM simulates a series of networks to approximate an observed network.

parameter values estimated using MLE; and $\Delta\ (g(y))_{ij}$ represents the change in g(y) when the relationship between *i* and *j* is toggled on or off.

For simplicity, suppose a researcher wishes to assess how edge formation and potential triangles in a network (shared connections between three actors) impact the probability of the observed network. *Figure 6* shows an example of how adding a single tie impacts the number of triangles in a network, with dashed red lines representing the addition of a single edge and solid red lines denoting the triangles formed as a result. To model this phenomenon, *Equation 2* takes the following form:

$$logit(Pr(Y_{ij} = 1 \mid Y^C)) = \theta_1 * \Delta\, edges + \theta_2 * \Delta\, triangles$$

where $logit(Pr(Y_{ij} = 1 \mid Y^C))$ represents the natural logarithm of the odds ratio of the probability of an edge existing versus the probability of an edge not existing; θ_1 represents the parameter coefficient for edge formation; $\Delta\, edges$ represents the change in total number of edges in the network when a single edge is added to the network (this value is always one as an addition of any edge to a network increases the total number of edges by one); θ_2 represents the parameter coefficient for triangle formation; and $\Delta\, triangles$ represents the change in total number of triangles in the network when a single edge is added to the network.

Figure 6

Edge and Triangle Formation using ERGM

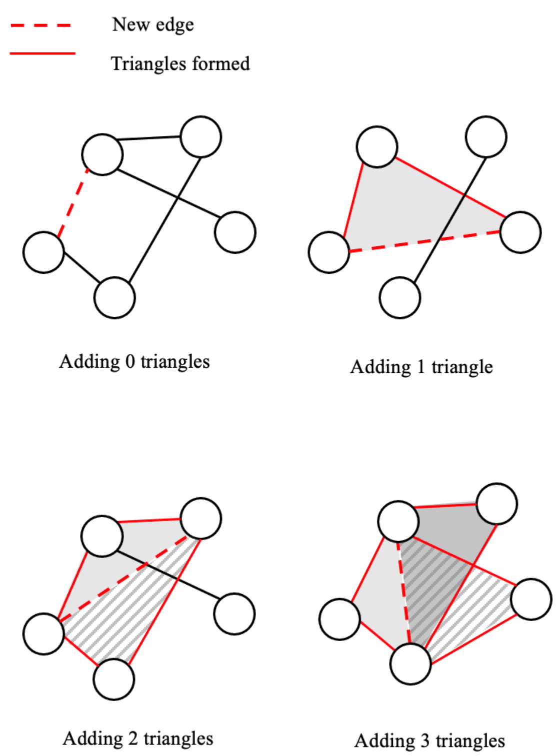


Figure 6. Mathematical visual of the impact that adding a single edge to a network has on triangle formation.

As an example of ERGM, a network can be simulated in R using the *statnet* package to (Handcock, Hunter, Butts, Goodreau, Krivitsky & Morris, 2018). After running a simple ERGM specifying the edges and triangle term, θ_1 (edge formation) is equal to 1.78 and θ_2 (triangle formation) is equal to -0.64. To show how the observed network probabilities change when assessing how additional edges impact the number of triangles in a network, the following equation is used, with mathematical results shown in *Table 2*:

$$logit(Pr(Y_{ij} = 1 \mid Y^C)) = exp(1.78 * \Delta\, edges + -0.64 * \Delta\, triangles)$$

Table 2

Example of ERGM Triangle Formation Mathematics

Triangles Formed	Equation	Logit	Probability
0	$logit(Pr(Y_{ij} = 1 \mid Y^C)) = 1.78 * 1 + -0.64 * 0$	1.78	0.86
1	$logit(Pr(Y_{ij} = 1 \mid Y^C)) = 1.78 * 1 + -0.64 * 1$	1.14	0.76
2	$logit(Pr(Y_{ij} = 1 \mid Y^C)) = 1.78 * 1 + -0.64 * 2$	0.50	0.62
3	$logit(Pr(Y_{ij} = 1 \mid Y^C)) = 1.78 * 1 + -0.64 * 3$	-0.14	0.47

Thus, the probabilities that the addition of a single edge in network Y will add zero, one, two or three triangles to the observed network are 0.86, 0.76, 0.62, and 0.47, respectively. A researcher could then statistically conclude that if an edge does not make a triangle in network Y, then its probability is 86%; if an edge adds one triangle to network Y, then its probability is 76%; if an edge adds two triangles to network Y, then its probability is 62%; if an edge adds three triangles to network Y, then its probability is 47%. This suggests that for the observed network, adding a single edge to the network is not likely to create more than two triadic relations.

Researchers and practitioners may use ERGM to begin to postulate about what social processes result in connections in a team. A negative effect for the change in the number of triangles suggests actors in a team connect with one another without forming triangular exchange patterns. Yet, with one observation of a team's network, ERGM cannot speak to how connections between actors in a team may change as actors collaborate with each other to perform their work. Observing team networks over time offers additional insights into how teams operate. To take advantage of observing networks over time requires dynamic network models.

Separable Temporal Exponential Random Graph Models

A useful extension of traditional ERGM that addresses the static limitations of ERGM is Separable Temporal Exponential Random Graph Modeling (STERGM). Rather than aggregating data collected over time to obtain a snapshot of a network, STERGM considers changes actors experience between time points that result in various network patterns (Leifeld & Cranmer, 2015). The goal of STERGM is to capture the dynamic properties of network evolution by specifying the ways in which edge formation and dissolution occur separately (Hanneke, Fu, & Xing, 2016; Morris et al., 2019). This approach facilitates the study of individual and structural processes that form networks over time (Liefeld & Cranmer, 2015).

STERGM Theoretical Foundation. While ERGMs provide a general framework for modeling a static network descriptively, they are unable to assess the evolution of a network over time (Guo, Hanneke, Fu, & Xing, 2007). To address this limitation Temporal Exponential Random Graph Modeling (TERGM) was introduced. The foundation of TERGM is built on panel regression such that, using a sequence of observations, prior network observations are used as predictors of subsequent network phenomena (Robins & Pattison, 2001; Block et al., 2018). TERGM models the temporal evolution of a network by modeling a given network based on all previously observed networks to capture dynamic properties that govern network change over time (Guo et al., 2007). Using TERGM, researchers can assess the network patterns that explain relationship formation over time (i.e., *formation*) and the network patters that explain relationship maintenance over time (i.e., *persistence/dissolution*; Krivitsky & Handcock, 2014).

Using TERGM as a foundation, STERGM provides a temporal extension to ERGM with the ability to separate parameters for relation formation and dissolution. STERGM combines two intermediate processes: the formation and dissolution of local network structures (Zhou et al., 2020). As with ERGM, the methodological core of STERGM is an edge embedded within a social structure, making the unit of analysis at the edge level (Block et al., 2018). STERGM assumes edge formation and edge dissolution are "separable" over time in the sense that edge formation is independent of edge dissolution *within* time points (Morris et al., 2019). The social mechanisms that contribute to relation formation are presumably different than the social mechanisms that contribute to relation termination. For example, friendship relations may form due to similarity in age, but relations may dissolve over time due to differences in hobbies and values (Krivitsky & Handcock, 2014). This differential specification of mechanisms that produce and terminate relations allows for the study of edge prevalence, incidence, and duration simultaneously, providing a basis for examining network dynamics (Krivitsky & Handcock, 2014).

STERGM jointly models the formation and dissolution of edges. It is assumed that edge formation and dissolution are conditionally independent *within* timesteps but are modeled dependently over time (Krivitsky & Handcock, 2014). STERGM models the phenomenon of actors entering and leaving a network by conducting separate TERGMs for formation and dissolution. In modeling network structures, the primary utility of STERGM is to show that structures exist more than expected by chance, controlling for the past where the past carries some dependencies (Block et al., 2018). STERGM can be used to explain the structure of an observed network, especially when previous network states are considered (Block et al., 2018).

STERGM Mathematical Foundation. Using the foundational conceptual map for dynamic network models, *Figure 7* describes the key terms modeled in STERGM. As STERGM allows for examining networks over time, it includes (F) time. (C) represents individual characteristic attributes, represented by triangular or circular shapes. (A) and (B) denote example sending and receiving actors, respectively. For simplicity, the (D) network structure focuses on the formation and removal of edges in which (1) a solid black line represents existing edges, (2) a solid red line represents edges formed and (3) a dashed red line represents edges removed. *Figure 7* models the propensity for edges to occur based on attribute homophily (sharing the same value on an attribute) and time. In addition to modeling all ERGM terms, STERGM includes temporally dependent terms.

Table 3 provides examples of temporally sensitive STERGM terms (Leifeld et al., 2018). Positive autoregression models the likelihood that edges will persist between time periods. Dyadic stability models the likelihood of present (non-present) edges at one time to remain present (not present) at a subsequent time. Edge innovation and loss model the

Figure 7

Conceptual Foundation for STERGM

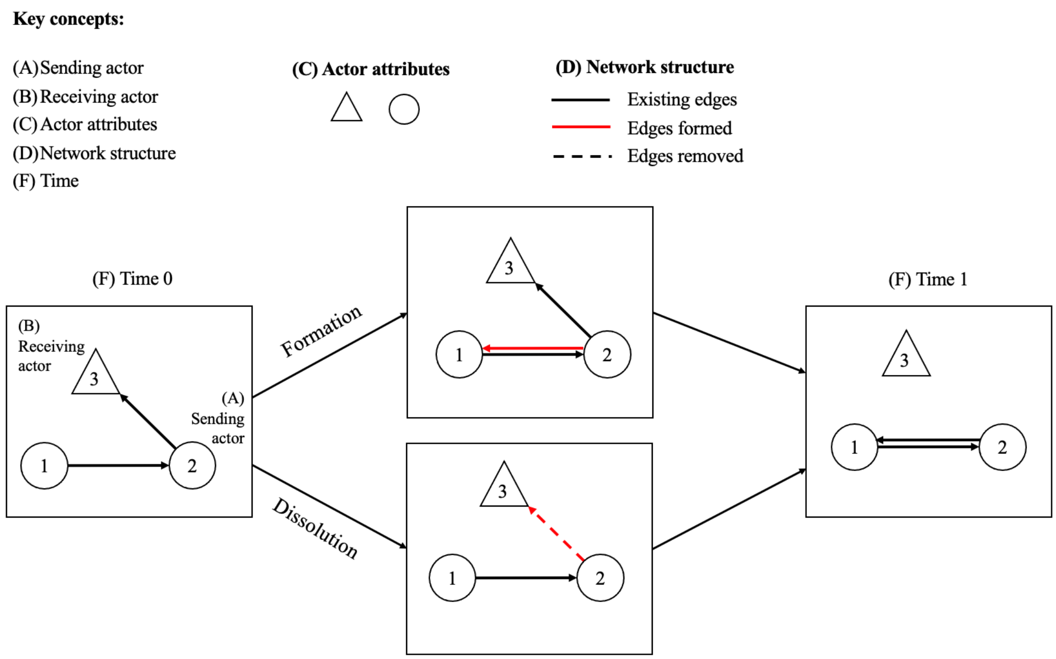


Figure 7. This figure represents a simple example of STERGM, including sending actors, receiving actors, an actor attribute, and the network structure/actions of forming and removing edges over time.

tendency for new edges to form (innovation) or old edges to dissolve (loss). A time covariate checks which type of time trends, if any, exist in the network (e.g., linear or quadratic trends). A time by covariate interaction term models the interaction between a time trend and a given model covariate (e.g., an actor attribute).

Table 3

Sample of Temporally Dependent STERGM Terms

Model Term	Description	General Example
Positive autoregression (lagged outcome network)	Models the persistence of edges between time periods	How many edges persist between time periods?

Dyadic Stability	Models the likelihood of present (non-present) edges at one time to remain present (non-present) at a subsequent time; like positive autoregression except this model term includes persistence of non-existing relationships	How stable are the connections in this network over time?
Edge innovation and loss	Models the tendency for new edges to form (innovation) or old edges to dissolve (loss) between time periods	How likely is it for new relations to form or for old relations to dissolve?
Time Covariate	Checks the type of time trend in the network, if one exists (e.g., linear, quadratic, geometric decay)	Is there a time trend for the number of edges that form over time?
Time by Covariate Interaction	Models the interaction between a linear time effect and a given model covariate	Does an effect of an actor attribute on edge formation change over time?

To show these effects, STERGMs take the following form for its formation and dissolution networks, respectively:

$$Pr\,(Y^t;\ \theta^+)\ = \frac{exp\{\theta^+ g^+(y^+, X)\}}{\sum_{y' \in y} exp\{\theta^+ g^+(y^+, X)\}} \tag{3}$$

$$Pr\,(Y^t;\ \theta^-)\ = \frac{exp\{\theta^- g^-(y^-, X)\}}{\sum_{y' \in y} exp\{\theta^- g^-(y^-, X)\}} \tag{4}$$

where y ∈ *y* represents a random graph, X is a vector of attributes, $\theta^{+(-)}$ represents the model parameters (θ) for the formation (+) model (dissolution (-) model), and $g^{+(-)}(y^{+(-)}, X)$ represents a function which returns a vector of sufficient statistics. The denominator represents a summation over the space of possible networks, *y*, on *n* nodes. Coefficients are modeled using MLE, identical to ERGM processes. This equation multiplies individual network probabilities to create a probability of the list of consecutive networks, allowing, but not requiring, each individual network probability to depend on the previous network observations (Czarna, Leifel, Śmieja, Dunfer, & Salovey, 2016).

For simplicity, suppose we are interested in modeling the behavioral patterns of relationship mutuality and transitivity (the clustering of three actors) over three time points for a hypothetical friendship network. To show an example, we can use a sample data set presented by Morris et al. (2019). The parameters to be specified are an edges parameter (edges), a reciprocity parameter (mutual), and a transitivity parameter (transitivity). Like ERGM, STERGM uses MLE to estimate model parameters. A STERGM specifying these parameters results in model output for both the formation model and the dissolution model (Handcock et al., 2018). Parameters for the two models are shown in *Table 4*. For the formation model, indicated by the terms "Form~*model term*," the mutual parameter emerges as a significant indicator of edge formation. For the dissolution model, indicated by the terms "Persist~*model term*," the transitivity parameter emerges as a significant indicator of edge dissolution.

Table 4

STERGM Example Model Parameters

Model term	θ
Form~Edges	-3.50*
Form~Mutual Ties	2.00*
Form~Transitive Ties	0.29
Persist~Edges	0.20
Persist~Mutual Ties	0.70
Persist~Transitive Ties	0.41*

Note. * = significant at p <.10

Probabilities for the formation and dissolution models are shown in *Table 5*. Given mutual ties emerged as a significant indicator of edge formation and transitivity emerged as a significant indicator of edge dissolution, the focus will be on these two parameters. Edge dissolution can be thought of as edge *persistence* such that model coefficients demonstrate the probability that a given parameter has edges persisting between time periods (Morris et al., 2019). Results indicate that all else being equal, there is an 88% chance a relationship will *form* if it closes a mutual pair (a reciprocal relationship) based on the model log odds of 2.00, and there is a 60% chance a relationship will *persist* if it closes a triadic relationship based on the model log odds of 0.41 (Morris et al., 2019). Essentially, for the hypothetical network observed, friendships tend to form when the friendship is mutual (i.e., both individuals want to form a relationship), but for relationships to be maintained, it is helpful to have a mutual friend (creating a friendship triad).

Table 5

Example STERGM Corresponding Probabilities

Model	Parameter	Log Odds	Probability
Formation Model	Mutual Ties	2.00	0.88
Persistence Model	Transitive Ties	0.41	0.60

STERGM facilitates the study of dynamic network phenomena. With respect to teamwork, researchers and practitioners may use STERGM to study the dynamics of team interactions. STERGM may represent how team member attributes affect team interactions and how team interactions form and persist over time. Separately considering the formation and dissolution of relations provides clearer insight into team functioning by allowing an examination of differential behaviors responsible for team interactions.

Stochastic Actor-Oriented Models

Stochastic Actor-Oriented Models (SAOM) represent network evolution using an actor-based simulation consisting of mini-steps (Ripley, Snijders, Boda, Vörös, & Preciado, 2021). Whereas STERGM utilizes simulation to identify the likelihood of given events occurring based on the observed network, SAOM models the evolution of a network that occurs *between* observed time points (Leifeld & Cranmer, 2015). SAOM is primarily used to model the statistical influences that determine the creation or termination of edges in a network based on individual behaviors (Snijders, 2016). The actor-orientation of this modeling framework implies all changes in relational edges are determined by actors within the network (Snijders, 2016).

SAOM Theoretical Foundation. SAOM is based on the notion that change stems from individual actors, making SAOM an actor-oriented model rather than an edge-oriented model, like STERGM (Block et al., 2018). Specifically, SAOM models the propensity for actors to form or maintain relations based on their surrounding network structures from an individual actor's perspective. Thus, SAOM is a micro-level analysis that allows for modeling change from an actor's point of view (Block et al., 2018).

At its core, SAOM focuses on the social structures and relations that are selected from the perspective of a given actor, making the unit of analysis at the individual level (Block et al., 2018). This positions SAOM as unique to other dynamic network models as it assumes every actor has agency to make individual choices that impact the rest of the network. SAOM implies that an actor's decision to create an edge is concurrently a decision against doing something else, like removing another edge, at a given time. The decisions actors make can also be expressed as the evaluation of edges in reference to how they are embedded within an actor's local network. This brings model specification closer to psychological theory as edges within the same network can be guided by different model parameters (Block et al., 2018).

SAOM analyzes change and network evolution. This positions SAOM to explore the bottom-up process of individual behavior driving network structures. SAOM is valuable in answering questions about the evolution or change in a network between two time points given that SAOM directly models a process that allows for direct inference of underlying social mechanisms for micro-level phenomena (Block et al., 2018). SAOM is widely used in a variety of social science disciplines to examine how individual behaviors lead to collective phenomena, such as international relations, policy, and other areas of political science (Snijders, 2016). As SAOM represents network evolution, it is well-suited for seeing how relations are maintained, enhanced, or eliminated over time.

SAOM Mathematical Foundation. Using the foundational conceptual map for dynamic network models, *Figure 8* describes the key terms modeled in SAOM. SAOM includes time (F) as it allows for examining networks over time; an actor attribute (C) differentiated on two values, a triangular and a circular shape, with sending (A) and receiving (B) actors; the network structure (D) which includes the creation, maintenance, or dissolution of edges where (1) a solid black line represents edge creation, (2) a solid gray line represents edge maintenance, and (3) a black dashed line represents edge dissolution. *Figure 8* models the propensity for edges to occur based on attribute homophily and time. For example, at Time 2, Actor 4 elects to create a new edge to Actor 3 with whom Actor 4 shares an attribute (i.e., both are circles).

SAOM posits that changes in actor attributes and/or network edges transpire in continuous time even though data are analyzed at discrete time points (Kalish, 2020). SAOM estimates what occurs between these discrete time points by breaking them into a series of mini-steps. A mini-step is an opportunity for a randomly selected actor to change either his outgoing edges or his level on a given attribute. SAOM posits an infinite number of mini-steps can occur between time points, and the number is determined by the amount of change that occurs in the observed networks between those time points (Leifeld & Cranmer, 2015).

Figure 8

Conceptual Foundation for SAOM

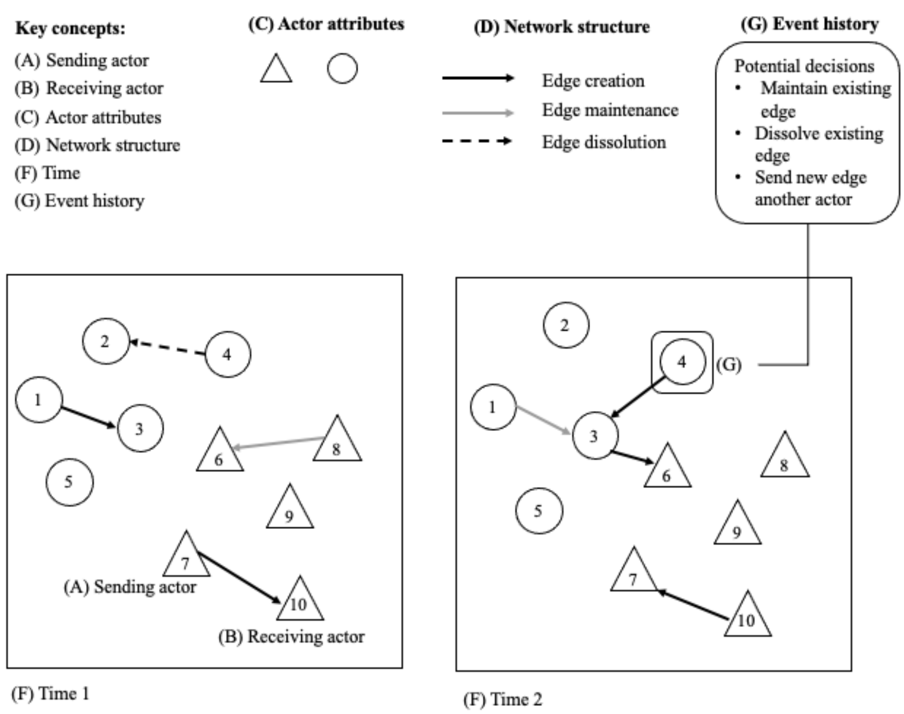


Figure 8. This figure represents a simple example of SAOM, including sending actors, receiving actors, actor attributes, and the network structure/actions of forming, maintaining, and removing edges over time.

There are two components that govern decisions made between time points: decision *timing* and decision *rules* (Schaefer, 2016). Decision timing models *if* change occurs, and decision rules model *what* change occurs. These two components are further broken into decision *types* – specifically, *network* versus *behavioral* evolution. Actors can control their outgoing edges and their behavior, and these decisions are dictated by the functions shown in *Table 6*. Decision timing is determined by the *rate function*, which determines (a) if there will be an opportunity for actors to make a change between given time points, and (b) who will make a change. Decision rules are determined by the *objective function*, which assesses the probability of a given change happening once an actor is selected to make a change. There are two decision *types* that actors can make in relation to decision timing and rules. An actor can decide to change either (a) his outgoing edges or (b) the level of a given attribute. Changing an outgoing edge leads to *network evolution* and is modeled through a network mini-step; changing the level of an attribute leads to *behavior evolution* and is modeled through a behavioral mini-step.

Table 6

Components of SAOM

	Decision Timing	**Decision Rules**
Network Evolution	Network rate function	Network objective function
Behavior Evolution	Behavior rate function	Behavior objective function

Note. Adapted from Schaefer (2019).

If an actor chooses to change his network, he has three options for change via network functions: (1) to create a new edge, (2) to maintain an existing (or non-existing) edge, (3) or to dissolve an existing edge, as shown in *Table 7*. These network functions refer to any endogenous network or selection effects that relate to the network itself, such as reciprocity, transitivity or homophily (Schaefer, 2019). Alternatively, an actor may decide to change his level on a given attribute, including any attitude or belief, via behavior functions. Behavior functions refer to a set of behavioral tendencies (Burke et al., 2007). Ultimately, an actor evaluates the outcome of each potential change based on how it impacts his objective function (Kalish, 2020).

Table 7

SAOM Network Mini-Step Decision Possibilities

Option	Time 1	Time 2	Definition
1	i j	i → j	Edge creation
2	i → j	i → j	Edge maintenance
	i j	i j	No-edge maintenance
3	i → j	i j	Edge dissolution

SAOM follows a six-step algorithm. *Figure 9* shows what occurs between two discrete, observed time points, specifically the iterative mini-step process (Schaefer, 2019):

(1) If the simulation is modeling what occurs between the first and second time point, the model initializes starting parameters.

(2) Actors draw selection propensities (or *waiting times*) for network and behavior options. Selection propensities are determined by the *rate function*. The rate functions will depend on attributes and network positions of the actors and will determine if there will be an opportunity for change to occur between two time periods. Each actor, *i,* has a rate of change for both network and behavioral change (λ), denoted $\lambda_i(x;\rho)$ where x represents the current state of the network and ρ represents a statistical parameter that depends on a

Figure 9

Conceptual Representation of SAOM Algorithm

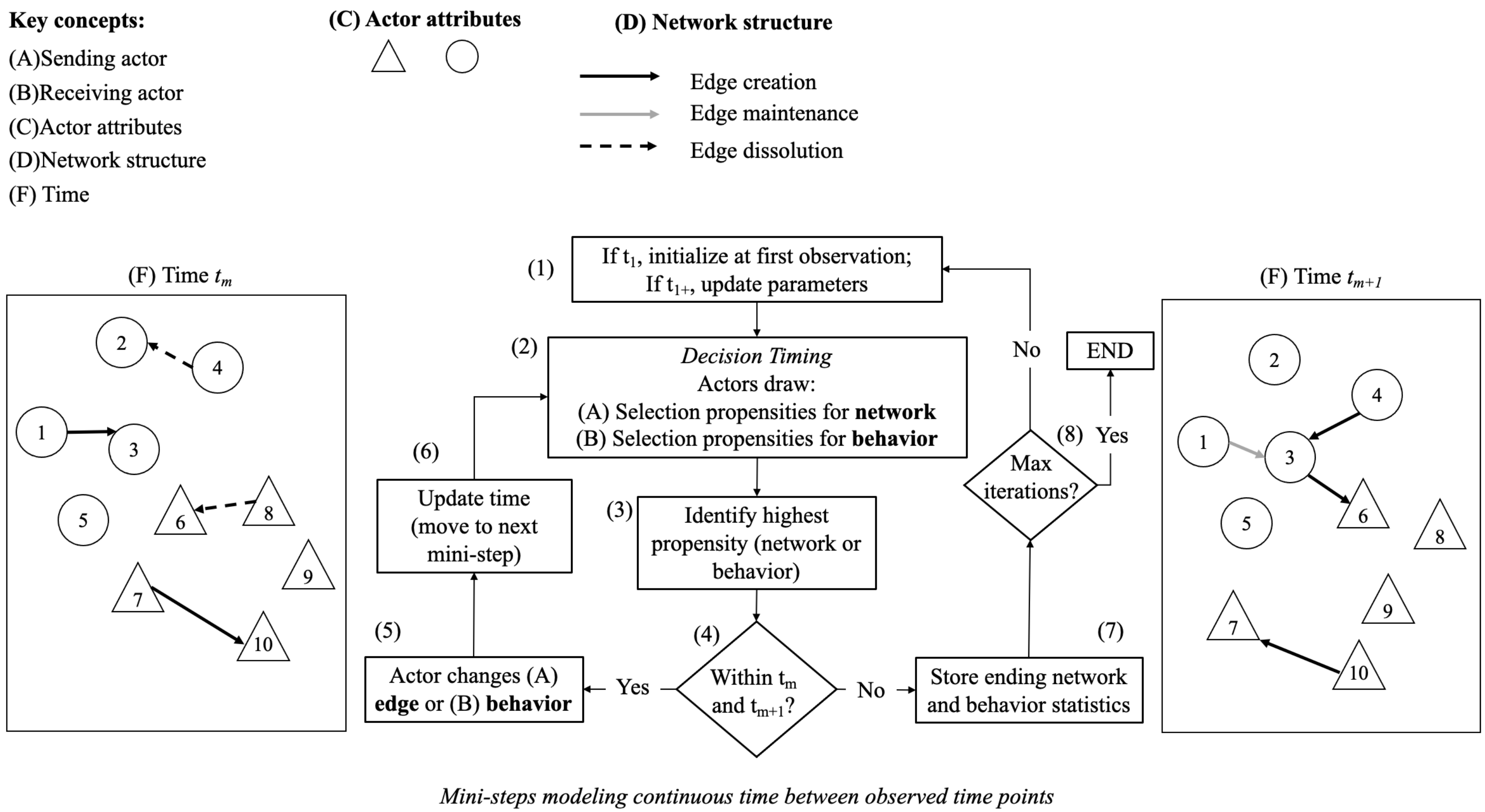


Figure 9. This figure represents a conceptual representation of the SAOM algorithm, including sending actors, receiving actors, actor attributes, and the network structure/actions of forming, maintaining, and removing edges over time. The algorithmic simulation occurs between any two given time points and includes six steps: (1) initializing the simulation, (2) decision timing, (3) identifying decision propensities, (4) checking simulation time clock, (5) change network or edge or (7) storing statistics, (6) updating time and moving onto the next mini step or (8) assessing number of remaining iterations.

(3) given time point (Snijders, 2016). Waiting times are drawn from an exponential distribution,

$$1 - exp\,(-\lambda\Delta t)\,, \tag{5}$$

where $\lambda = \lambda_{+}(x;\rho)$, representing the sum of the change rates for all actors. Smaller rates represent lower selection propensities for an action, and higher rates represent higher selection propensities. Selection propensities are drawn for both network change (λ_{net}) and behavior change (λ_{beh}). If a change is determined by the exponential distribution, the probability that the next opportunity for change for actor *i* is given by

$$\frac{\lambda_i(x;\rho)}{\lambda_{+}(x;\rho)}$$

which represents the rate of change for actor *i* divided by the sum of change rates for all actors in the network.

(4) The actor with the highest selection propensity, which can be for network or behavior change, is identified. These rates can differ based on both network and actor attributes (Schaefer, 2019).

(5) The simulation checks that enough time remains between t_m and t_{m+1} (the time point in question) for another action to occur using the selection propensities.

(6) If enough time remains within t_m and t_{m+1}, the *objective function* is calculated to determine the probability of a given change happening. This calculation will depend on whether the waiting time selected is for network or behavior change. The network objective function takes the following form:

$$f_i(x,z) = \sum_k \beta_k s_{ik}(x,z) \tag{7}$$

where $f_i(x, z)$ represents the value of the objective function for actor i for a given network state x with attributes z; β represents parameter estimates for k parameters; parameter values β are coupled to an effect, such as reciprocity, denoted as s_{ik}. The behavior objective function takes the following form:

$$f_i(x, z) = \sum_k \beta_k s_{ik}(x, z) \tag{8}$$

where $f_i(x, z)$ represents the value of the objective function for actor i for a given network state x with attributes z; β represents parameter estimates for k parameters; parameter values β are coupled to an effect, such as behavioral similarity, denoted as s_{ik}.

(6) Following step 5 (the completion of calculating an objective function that maximizes the probability of a given network or behavior change to occur), the simulation moves to the next mini-step such that the algorithm loops back to step 2 (drawing decision timing from an exponential distribution).

(7) The simulation continues until no time remains for additional action. At this point, the simulation stores the ending network and behavioral statistics calculated during the entire period across actors and their respective mini-steps.

(8) The simulation checks it has reached a maximum number of iterations (predefined in the algorithmic process). If the simulation has *not* reached its maximum iterations, the simulation starts back at the first step by updating simulation parameters for the next iteration in an attempt to minimize the deviation of the final network within time t from the true observed data at

t_{m+1}. If the simulation has reached its maximum iterations, the simulation for timepoint t ends.

Data from the simulation are assessed for convergence such that the model can reproduce the observed network and behavior at time t_{m+1}. If convergence is not reached, the model is to be rerun with new starting values to attempt to better represent reality. Once convergence is reached, goodness of fit is calculated to compare networks generated by the model to statistics that are not explicated within the model (Schaefer, 2019).

To show an example of SAOM, *Table 8* represents a basic matrix of edges in a small network, including edges at Time 1, edges at Time 2, and levels for an attribute at Time 1 and Time 2. A 0 represents no edge and a 1 represents an edge nomination from actors in the rows to actors in the columns. We observed that at Time 1, Actor C, an actor with a low value on an attribute, nominates Actor A, an actor who also has a low value on an attribute, and that this relationship is maintained at Time 2. Actor A, an actor with a low value on an attribute, nominates Actor B, an actor with a high value on an attribute, and this relationship is not maintained at Time 2. By Time 2, Actor A and Actor C, both with low values on an attribute, nominate each other, and Actor B does not give nor receive any nominations. Actor B's attribute value also increases at Time 2.

To assess the mechanisms that likely produced the network observed at Time 2, we follow the logic presented in *Figure 9*:

(1) Initialize parameters for the first observation.

(2) Actors A, B, and C draw waiting times for network and behavior options. These values are assessed using the *rate function* for both network and

Table 8

Example Data Structure Used in SAOM

Network Time 1				Network Time 2				Attribute	
	A	B	C		A	B	C	Time 1	Time 2
A	0	1	0	A	0	0	1	1	2
B	0	0	1	B	0	0	0	2	3
C	1	0	0	C	1	0	0	0	0

behavioral change (λ). Assuming λ_{net} is estimated to be 0.3 for each actor, λ_{beh} is estimated to be 0.08 for each actor, and that Δt equals 1, we use *Equation 5* to assess if there will be an opportunity for change:

$$1 - exp\ (-\lambda\ \Delta t)$$

Network change: $1 - exp\ (-0.3\ *\ 1) = 1 - exp\ (-0.3) = 0.25$

Behavioral change: $1 - exp\ (-0.08\ *\ 1)\ = 1 - exp\ (-0.08)\ = 0.08$

The resulting probabilities are 0.25 and 0.08, meaning there is a 25% chance that there will be an opportunity for a network change to occur and an 8% chance for a behavioral change to occur in this model iteration. Drawing from a uniform distribution with this parameter, the next step determines *who* will have an opportunity to make a change, which is accomplished using *Equation 6*:

$$\frac{\lambda_i(x;\rho)}{\lambda_+(x;\rho)}$$

$$Network: \frac{0.3}{0.3 + 0.3 + 0.3} = \frac{0.3}{0.9}\ =\ 0.33$$

$$Behavior: \frac{0.08}{0.08 + 0.08 + 0.08} = \frac{0.08}{0.24}\ =\ 0.33$$

The result is that each actor has a 33% chance of being selected to make a both a network and behavior change. These values represent the actors' propensity for change.

(3 – *Network Effect*) To model a network change, assume Actor A is selected to make a network change.

(4 – *Network Effect*) Assume that enough time remains for Actor A to make a change before Time 2.

(5 – *Network Effect*) Calculate the *objective function* for network effects. For simplicity, using *Equation 6*, the model assesses the objective function for two network changes: reciprocity and outdegree (number of connections sent to other actors). Assume parameter values for the reciprocity and outdegree effects are estimated to be -.08 and 1.2, respectively. Actor A can do one of the following: (1) create a new edge to Actor C, (2) drop his existing edge to Actor B, or (3) do nothing (maintain an existing edge to Actor B). The objective equation based on these parameters is as follows:

$$f_i(x,z) = \sum_k \beta_k s_{ik}(x,z)$$

$$f_i(x,z) = \theta_1 * Reciprocity + \theta_2 * Outgoing\ Edge$$

where θ_1 represents the reciprocity coefficient, θ_2 represents the outgoing edge coefficient, and the terms *Reciprocity* and *Outgoing Edge* will be replaced by a value representing whether the action adds an edge (+1), subtracts an edge (-1), or does not change the number of edges in the network (0). *Table 9* illustrates the objective function for each potential decision, and the value of the objective function based on those decisions.

Table 9

Example Network Objective Functions for Three Actor Decisions

Option	Reciprocal Edges	Outgoing Edges	Objective Function	Value of Objective Function
Create a new edge to Actor C	+1	+1	-.08*1 + 1.2*1	0.4
Drop existing edge to Actor B	0	-1	-.08*0 + 1.2*-1	-1.2
Maintain existing edge to Actor B	0	0	-.08*0 + 1.2*0	0

Note. +1 adds an edge; -1 removes an edge; 0 does not impact the number of edges.

Since Actor A is seeking to optimize his network objective function, he will most likely decide to create a new edge to Actor C (network objective function = 0.4).

(3 – *Behavior Effect*) To model a behavioral change, again assume Actor A is selected to make a behavior change.

(4 – *Behavior Effect*) Assume that enough time remains for Actor A to make a change before Time 2.

(5 – *Behavior Effect*) Calculate the *objective function* for behavioral effects. For simplicity, using *Equation 6*, the model assesses the attribute *similarity effect*, which captures the tendency of actors become more similar on a given attribute over time (Kalish, 2020). Using *Equation 8*, we model this effect as follows:

$$f_i(x,z) = \sum_k \beta_k s_{ik}(x,z)$$

$$f_i(x, z) = \underbrace{z_i}_{\text{Linear effect}} + \underbrace{z_i^{2}}_{\text{Quadratic effect}} + \underbrace{\sum_j x_{ij}\left(1 - \frac{|z_i - z_j|}{\text{range}(z)}\right)}_{\text{Similarity effect}}$$

The linear effect is included by default to control for the distribution, as is a baseline quadratic effect for an actor's own behavior if a behavior has more than two levels. The similarity effect assesses the similarity between behavior (z) for actor *i* and the actors that are connected to *i*. Assume parameters are estimated for the linear, quadratic, and similarity effects to be -0.25, 0.50, and 1.5, respectively. Actor A has three options for behavioral change: (1) to decrease his attribute value by one, (2) to not change his attribute value, or (3) to increase his attribute value by one (Schaefer, 2019). To assess the linear effect, a linear function is used such that the linear parameter ($\beta = -0.25$) is multiplied by potential attribute value levels. A quadratic function is applied to the quadratic effect such that the quadratic parameter ($\beta = 0.50$) is multiplied by the squared value of potential attribute value levels. Similarity effect calculations are shown in *Table 10*.

Table 10

Similarity Effect Calculation

Behavior Change Option	**Connection**	**Similarity Effect**	**Similarity Statistic**
Decrease attribute value to 0	Actor A, Actor B	1 – (|0-2| / 3) = 0.33	1.33
	Actor A, Actor C	1 – (|0-0| / 3) = 1	
Maintain attribute value at 1	Actor A, Actor B	1 – (|1-2| / 3) = 0.67	1.34

	Actor A, Actor C	1 – (|1-0| / 3) = 0.67	
Increase attribute value to 2	Actor A, Actor B	1 – (|2-2| / 3) = 1	1.33
	Actor A, Actor C	1 – (|2-0| / 3) = 0.33	

Table 11 shows the mathematics behind the three effects included in this example. The values in each equation represent (a) the beta values for a given effect and (b) the level of the attribute being assessed for each of the three potential decisions as calculated in *Table 10*. The final value of the objective function is the sum of each of the resulting effects. Based on the value of the objective function, Actor A will increase his attribute value by one to an attribute value of two, suggesting Actor A's attribute value is being impacted by attribute values of Actor B and Actor C.

(7) Actor A selects the action that maximizes his objective function (if network change, he will add an edge to C; if behavior change, he will increase his attribute value to two). The simulation will move to the next mini-step by looping back to step 2.

(7) The simulation continues until no time remains for additional action by the actors.

(8) Once the simulation reaches its maximum number of iterations for timepoint *t*, it will end.

Table 11

Example Behavior Objective Functions for a Similarity Effect

If the attribute value	Linear effect ($\boldsymbol{\beta = -0.25}$)	Quadratic Effect ($\boldsymbol{\beta = 0.50}$)	Similarity Effect ($\boldsymbol{\beta = 1.5}$)	Value of Objective Function

Drops to 0 (-1)	-0.25*0=0	0.50*(0^2)=0	1.5*1.33=2	2
Stays at 1 (0)	-0.25*1=-0.25	0.50*(1^2)=0.50	1.5*1.34=2.01	2.26
Increases to 2 (+1)	-0.25*2=-0.50	0.50*(2^2)=2	1.5*1.33=2	3.5

While STERGM and SAOM present much methodological overlap, there are two key differences between them. First, the primary focus of STERGM is on the probability of an edge occurring, whereas the primary focus of SAOM is on the probability of an actor impacting edges. Second, STERGM focuses on networks in discrete time to answer questions about *structure* whereas SAOM focuses on networks in continuous time to answer questions about *change* (Karell, 2018). Yet, information is inherently lost when aggregating events into time points (Butts & Marcum, 2017). Even when each individual event between two actors is captured, both SAOM and TERGM require data to be aggregated into specified time points (i.e., panel data) and analyze the relationship between and across time points rather than between each individual event. Moreover, researchers must determine the appropriate width of aggregation, which impacts the level of dynamic granularity.

Relational Event Models

A key limitation of STERGM and SAOM is that they fail to fully utilize continuous time data (Leenders et al., 2016). STERGM and SAOM require aggregating continuous data into discrete, observable time points. To overcome this limitation, *Relational Event Models* (REM) can handle both discrete and continuous time data. By examining data in continuous time, one may more granularly examine interactions over time (Schecter & Contractor, 2017).

REM Theoretical Foundation. REM incorporates networks and time into team processes and views these processes as relational *events* rather than relational states (Schecter et al., 2018). Relational events are the unique actions produced by an individual taking an action directed toward another individual (Pilny, Schecter, Poole, & Contractor, 2016). They occur at specific moments in time such that any given relational event is tied to a distinct time point. The ordering of episodic relational events is known as an *event history*. Examining event histories pushes dynamic network models beyond the individual or the edge level to the individual unit of a single interaction, providing the most nuanced examination of team processes amongst dynamic network models (Leenders et al., 2016; Schecter et al., 2018).

Figure 10 shows how models using a relational event framework are proposed based on theory, which is used to determine a set of possible events (i.e., event history) and the mechanisms that determine event hazards (Butts & Marcum, 2017). Event hazards are defined as the propensity of a given event to occur and are specified through an exponential function of a linear combination of statistics (Butts & Marcum, 2017; Schecter & Contractor, 2017).

REM is considered a micro-sequence analysis in that its focus is on *who interacts with whom* at a given time rather than focusing on what an entire group is doing at a given time (Pilny et al., 2016). When studying teams, REM offers a way to assess individual actions over time that produce event sequences that explain differences in team processes. REM is useful for studying theories of emergence as building theories of emergence requires focusing on the sequence and timing of team processes. Using an event history, REM connects emergent phenomena to different variables to understand

Figure 10

REM Framework

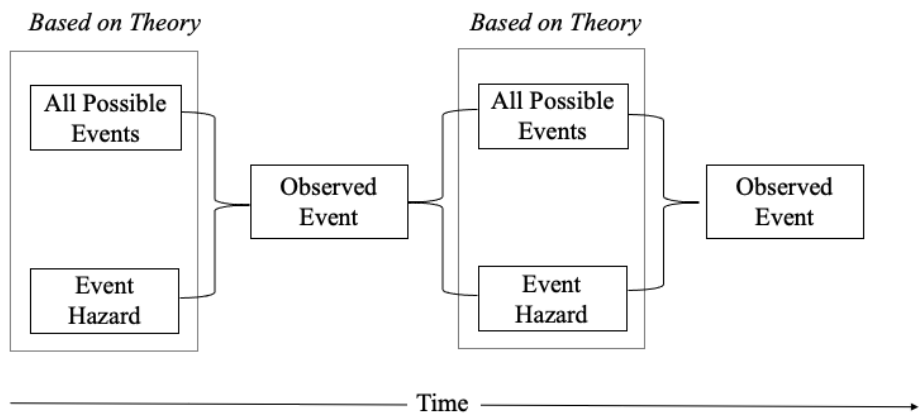


Figure 10. The relational event framework shows the notion of theory informing event propensities (i.e., event hazards) based on a set of possible events to explain an observed event. Event hazards are updated based on observed events.

the underlying processes responsible for emergent outcomes. By determining the exact sequence and timing of individual actions, REM can precisely specify process mechanisms (Kozlowski, 2015; Schecter et al., 2018). Understanding the variation in how different team processes unfold can enable researchers to begin explaining differences in the emergence of higher-order phenomena (Schecter et al., 2018).

REM Mathematical Foundation. REM assumes that past relational events influence subsequent relational events thus affecting their propensity (i.e., hazard rate) to occur (Butts, 2008). Actions that occur more frequently are said to have high rates of occurrence whereas actions that occur less frequently have lower rates of occurrence (Pilny et al., 2016). These rates additionally determine the amount of time that passes between interactions such that more frequent interactions result in a shorter interval between interactions. These rates are determined by model covariates, such as attributes of the actors and how these attributes interact with time.

Figure 11 presents the conceptual framework that governs relational events. To identify how and why relational events occur, REM considers influence from three factors: (1) past relational events, (2) actor attributes (3) and exogenous contextual factors. Past relational events, often referred to as "endogenous mechanisms," are the prior event sequences that impact the probability of the next relational event to occur. Examples include: (a) inertia, or how the combination of prior events for a given individual will influence future rates of that individual's behavior (e.g., tendency for past contacts to be future contacts); (b) reciprocity (e.g., tendency for Person A to send an event to Person B given that Person B just sent an event to Person A); (c) triadic closure in which three individuals form a clique-like structure based on prior events (e.g., if Person A and Person B both send events to Person C separately, what is the chance that Person A and Person B will interact?).

Figure 11

Conceptual Framework for Relational Events

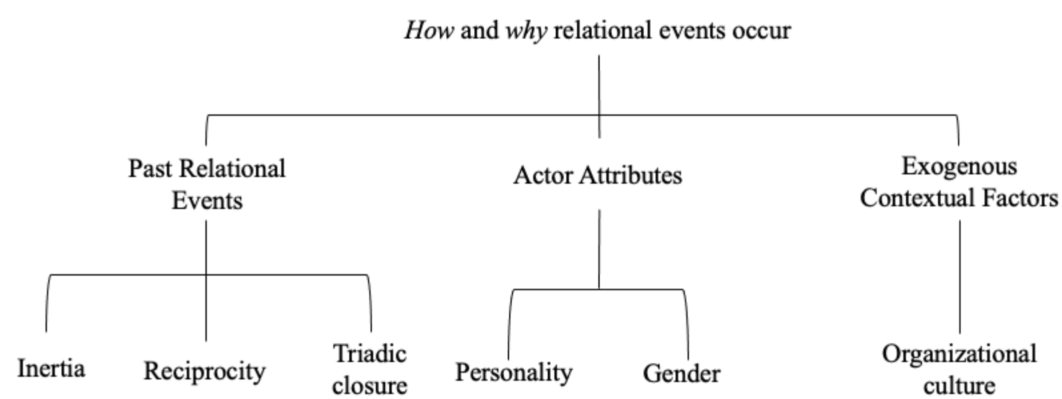


Figure 11. Adapted from Pilny et al., (2016). A conceptual representation of the relational events framework to explain how and why relational events occur based on past relational events, actor attributes, and exogenous contextual factors.

Actor attributes affect the propensity for interactions to occur based on an attribute of the sender, receiver, or event. Examples include attributes such as personality (e.g., does introversion result in increased outward communications?) or gender (e.g., are relational sequences the product of an individual's gender?). Exogenous contextual factors include any characteristic that is outside of past relational events or actor attributes (i.e., environmental events beyond the system). For example, organizational culture spans beyond the interaction space but impacts communication patterns such that teams within a collaborative culture are likely to interact more than teams within a non-collaborative culture (Pilny et al., 2016). Over time, the propensity of any given event to occur changes as the rate of any event is altered to reflect past actions. For example, if Person A receives consistent communications from two different individuals, Person B and Person C, the propensity for Person B and Person C to communicate to one another increases over time (Pilny et al., 2016). The event rates are continuously updated to account for changes in group interactions to provide insight into how past interactions impact the emergence of subsequent interactions.

Using the foundational conceptual map for dynamic network models, *Figure 12* describes the key terms modeled in REM. REM is primarily focused on examining event histories (Pilny et al., 2016), making the dependent variable an interaction event that occurs between a sending actor (A) and a receiving actor (B) over time (F) (Schecter et al., 2017). Each time point represents a single relational event in which a single actor makes a change to his or her network, and the aggregation of decisions made within each relational event comprise the event history. There are sending (A) and receiving (B) actors with attributes (C), denoted by triangles and circles. The network structure (D) includes the creation, maintenance, or dissolution of edges in which a (1) solid black line represents edge creation, (2) a solid gray line represents edge maintenance, and (3) a dashed black line represents edge dissolution. Decisions made by actors are driven by event histories (G) within the context of relevant external factors (E).

REM can represent several relational event tendencies. For example, REM can model a *participation shift* involving the propensity for an initial sender, Person A, to send an event to a recipient, Person B, and in turn, Person B can direct the next event to another actor, Person Y. *Table 12* provides example model terms for REM, including two types of participation shifts (i.e., PSAB-BA turn receiving and PSAB-BY turn receiving) and the effects of inertia, popularity, prior initiation patterns, and attribute homophily.

REM assumes events occur based on the realized history of previous events. This produces the context for future events that create differential propensities for subsequent relational events to occur (Butts, 2008). The realized history of previous events determines both the relative rates at which future events occur and the type of events that are possible. Relational event specification includes a set of potential senders, S, potential receivers, R, and potential action types, C (Butts & Marcum, 2017). A single relational event, a, is a tuple containing:

The sender of the action $s = s(a) \in S$,

The recipient of the action $r = r(a) \in R$,

The type of action $c = c(a) \in C$, and

The time the action occurred $\tau = \tau(a)$,

denoted as $a = (s, r, c, t)$ in which actions may include covariates (X_a) based on properties of event elements (e.g., sender and recipient; Butts & Marcum, 2017).

Figure 12

Conceptual Foundation for REM

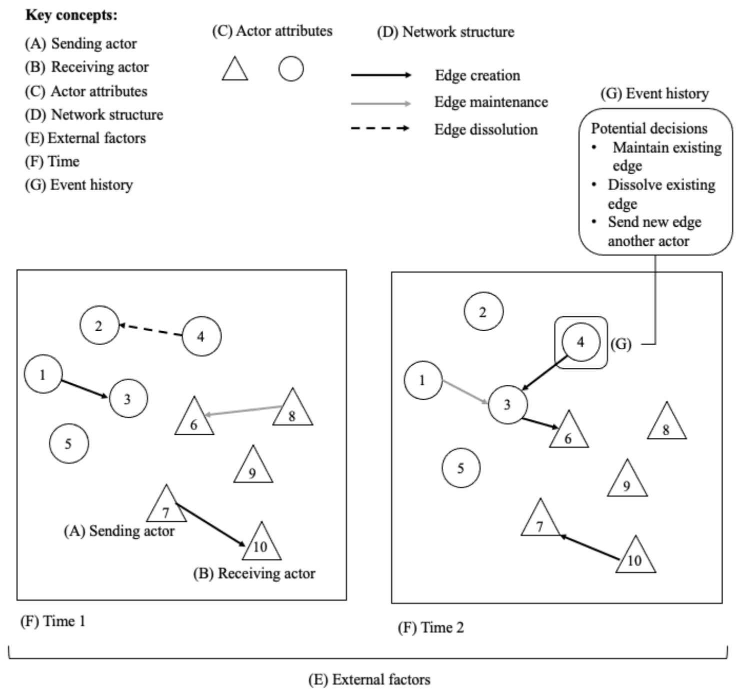
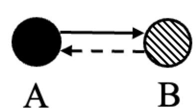
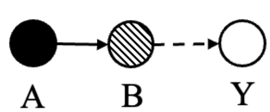
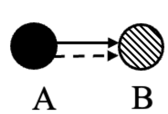


Figure 12. This figure represents a simple example of REM, including sending actors, receiving actors, the actor attribute of gender, the network structure/actions of forming, maintaining, and removing edges over time, event history, and external factors.

Table 12

Example REM Terms

Name	Visualization	Description
PSAB-BA Participation-shift (turn receiving)		An event from person A to B is followed by an event from person B to A
PSAB-BY Participation-shift (turn receiving)		An event from person A to B is followed by an event from person B to Y
Inertia		Person A initiates more events to Person B as a function of the number of past events from person A

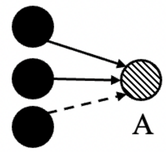
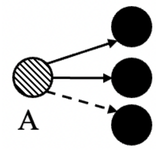
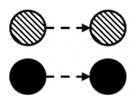
Popularity		Tendency of A to receive relational events based on how many prior relational events A has received
High initiator		Tendency of A to send many relational events
Attribute homophily		Tendency for individuals to send relational events to other individuals who are similar to them (e.g., gender, role, tenure)

Table 12. Visual REM representation adapted from Leenders et al., (2016). Solid lines represent past relations. Dotted lines represent future relations.

The set of possible events that can occur at any given point in an event history is known as the *support*, defined by the set of $A(A_t) \subseteq S\ x\ R\ x\ C$ where A represents the set of events that are possible at any given moment. Identifying the propensity of a specific relational event to occur requires specifying the event's *hazard* (Butts & Marcum, 2017). Each possible event, including events that previously occurred and events that could have occurred but did not, has a non-zero hazard, with larger hazards representing higher occurrence propensities. To infer these propensities, event hazards are parameterized based on a combination of factors that inhibit or enable the realization of an event:

$$\lambda_{aA_t\theta} = exp(\theta^T u(s(a)\,, r(a), c(a), X_a, A_t)) \quad (9)$$

where $\lambda_{aA_t\theta}$ represents the hazard of a potential event *a* at time *t* given event history A_t and θ represents a vector of model parameters; *u* represents a vector of statistics governed by $s(a)$, $r(a)$, C(a), X_a and A_t. *Figure 13* provides a visual adaptation of Figure 12's conceptual foundation for REM to represent the REM model statistics.

Figure 13

REM Conceptual Foundation with Model Terms

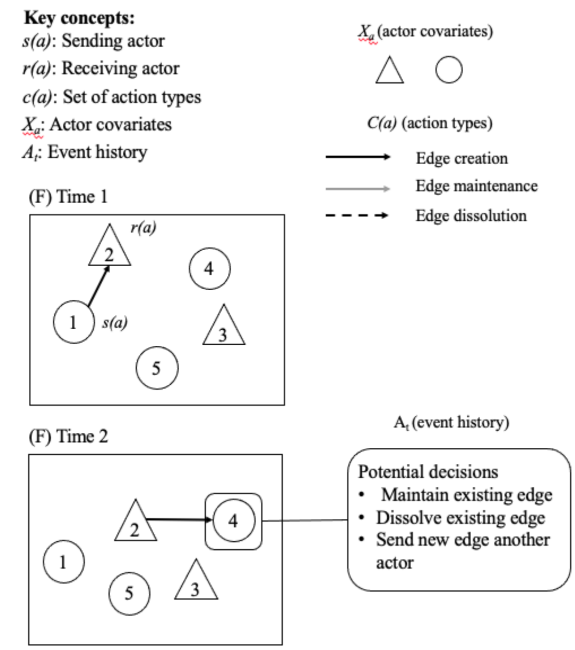


Figure 13. An adaptation from Figure 12 (conceptual foundation for REM) to highlight model statistics used in REM.

REM allows for the use of both continuous and ordinal time data (Butts, 2008). The data used in this dissertation are ordinal time data, which requires a different specification from continuous time data in REM. Thus, for this paper, REM specification is described in terms of ordinal time data (for an explanation of continuous time modeling using REM, see Butts, 2008). In the absence of exact timestamps on sequential data, the likelihood of events in event history A_t are based on the possibility of given events that occur next in a t-directed sequence. The probability that a_i, or the conditional likelihood that a given event i occurs next in an event sequence, equals the occurrence rate for a_i divided by the sum of the rates for all possible events that could occur (including a_i).

Given successive events are conditionally independent, the likelihood of event history A_t is a product of multinomial likelihoods, specified as:

$$p(\theta) \; = \prod_{i=1}^{M} \left[\frac{\lambda_{a_i A_{\tau(a_{i-1})} \theta}}{\sum_{a\prime \, \epsilon \, A(A_{\tau(a_i)})} \lambda_{a\prime A_{\tau(a_{i-1})} \theta}} \right] \tag{10}$$

where $p(\theta)$ represents the probability of an event history A_t to occur given some model parameters θ; $\prod_{i=1}^{M}$ represents the series product of non-null events (M), beginning with the first event (i = 1); $\lambda_{a_i A_{\tau(a_{i-1})} \theta}$ represents the occurrence rate of event a_i (λ_{a_i}) given event history (A_t) up to the prior event ($a_{i\text{-}1}$) governed by model parameters defined by θ; $\sum_{a\prime \, \epsilon \, A(A_{\tau(a_i)})} \lambda_{a\prime A_{\tau(a_{i-1})} \theta}$ represents the sum of the rates for all possible events that could occur, governed by the sum of possible relational events (a') that are an element of (∈) all possible relational events at a particular time period (A).

Figure 14 shows an example event sequence between three actors, Actor A, Actor B, and Actor C, at three discrete time points (Brandenberger, 2020). The relationships above the center line represent true events (*observed events*), whereas the relationships below the center line represent all other potential events that could have occurred in place of the observed event (*null events*). Given three actors, at each time point there are six potential sender-receiver options (three senders x two potential recipients at any given time).

Table 13 shows the first five rows of a relational event sequence of communications for a team of 15 individuals, labeled A through J, including the time of the event, the sender, the recipient, and the action type. Assessing the explanatory

Figure 14

Example Relational Event Sequence

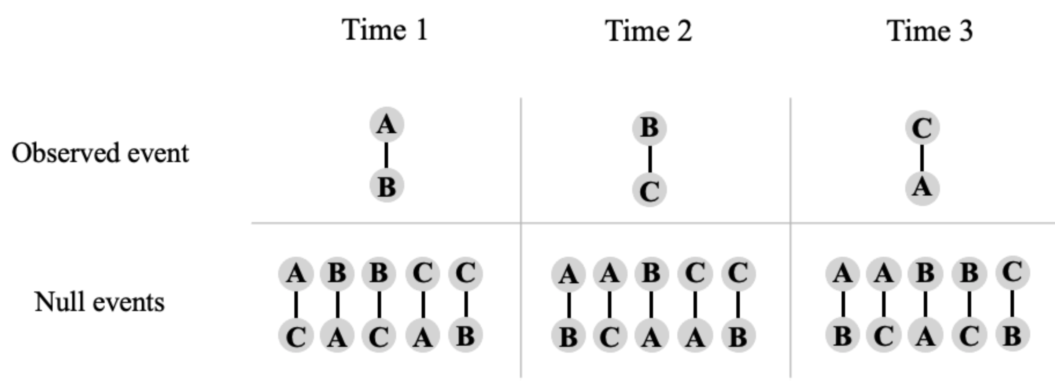


Figure 14. Example REM event sequence showing observed events at three discrete time points. Adapted from Brandenberger (2020). Null events represent all remaining potential events that could have occurred in place of the observed event.

mechanisms that produced the observed event history requires specifying model effects. In this example, participation-shifts PSAB-BA (a reciprocation effect), PSAB-BY and PSAB-AY are examined. Each of these relational events are assigned a rate based on estimated model parameters, θ, calculated based on the observed data (i.e., *s(a)*, *r(a)*, *C(a)*, X_a, and A_t) via Maximum Likelihood Estimation (MLE).

Table 13

Example Relational Events Sequence

Time	Sender	Recipient	Type of Action
1	A	D	Outgoing message
2	B	E	Outgoing message
3	E	A	Outgoing message
4	H	E	Outgoing message
5	B	D	Outgoing message

Table 14 shows resulting parameter estimates for the three specified participation shifts. Parameter estimates represent the logged multiplier for the hazard of an event, which, when transformed exponentially, represents a hazard rate relative to other events that could occur. In this example, the PSAB-BA coefficient suggests that reciprocated events have 1.6 times the hazard of other event types whereas the PSAB-AY coefficient suggests that communication from A to B followed by communication from A to Y has a much smaller hazard. This suggests that for this team, reciprocity is the most prevalent communication sequence to occur at any given point throughout the time observed.

Table 14

REM Example Model Parameters

Model Term	Estimate	Hazard Transformation	Resulting Hazard
PSAB-BA	0.52	exp(0.52)	1.60
PSAB-BY	0.24	exp(0.24)	1.27
PSAB-AY	-0.39	exp(-0.39)	0.68

REM uses an evolutionary approach in which lower-level behavioral patterns are modeled, making it well-suited for studying process theories and capturing emergence (Schecter et al., 2017). Specifically, it seeks to understand the specific behaviors that drive what will occur next in a sequence of events (Butts & Marcum, 2017). By assessing interactions at the individual communication level, REM identifies the exact behavioral patterns that are most likely to drive future interactions. This positions REM to quantify process more directly (Butts, 2008; Schecter & Contractor, 2017), which is a key requirement for studying emergence (Grand et al., 2016).

Comparative Utility of Dynamic Network Models

The three dynamic network models described in this dissertation offer relatively distinct approaches to studying networks dynamically. *Table 15* provides a comparison of the utility of each model, focusing the unit of analysis, outcome level, purpose, an example question, and the data required for each method. The three models essentially represent a hierarchy of temporal resolution and unit of analysis (Schaefer & Marcum, 2017). STERGM is conducted at the edge level of analysis with a network as the outcome and requires whole network data broken into longitudinal networks to assess change over time. This lends STERGM to answer questions about how individual actors, edges, and actor covariates impact how edges form and dissolve within networks. An example question STERGM can answer is, "how do individual attributes impact edge formation and dissolution over time?" STERGM can assess how individual differences within a team differentially impact the types of relations that form within teams. More concretely, suppose a researcher wanted to study homophily, or the phenomenon in which contact between similar individuals occurs more frequently than between dissimilar individuals (McPherson, Smith-Lovin, & Cook, 2001). To examine, for example, homophily of team role, researchers can use STERGM to answer the question of how this attribute impacts team relations over time, as outlined below:

(1) Researcher collects relational data for a team over time, including edge formation, dissolution, and demographics (e.g., team role).

(2) Researcher breaks data into logical time periods of interest (e.g., five time periods).

Table 15

Comparative Utility of Dynamic Network Models

	Dynamic Network Model		
	STERGM	**SAOM**	**REM**
Unit of analysis	Edge	Individual	Edge
Outcome level	Network	Individual and network	Network
Purpose	Assess the effects of actors, edges, and covariates of network structures on how edges form and dissolve	Assess the effects of actors, edges, and covariates of network structures on how edges form and dissolve; assesses multiple types of relations in a single model and addresses question about how network structure impacts actor attributes	Assess sequencing, patterns, timing, and likelihood of social events
Example question	"How does the impact of individual attributes on edge formation and dissolution change over time?"	"How do individual attributes change over time based on team interactions?"	"What sequence of team behaviors drives what will occur next?"
Data required	Whole network broken into longitudinal panels	Whole network broken into longitudinal panels	Ordinal or continuous series of social interactions

Note: Adapted from Schaefer & Marcum (2017).

(3) After cleaning and formatting the data, the researcher runs a STERGM that includes terms for an attribute (e.g., team role), time, and the interaction of time and an attribute.

(4) STERGM produces theta values for effects to calculate probabilities for edge formation and dissolution.

(5) Researcher interprets the theta values to understand what impacts edge formation and dissolution.

STERGM enables the study of dynamic network phenomena and facilitates knowledge of team process over time by specifying two separable interaction channels responsible for a team's relational behaviors that are differentially impacted by individual attributes, network structural effects, and team context. This distinction allows for examination of social mechanisms that occur within teams that result in relation formation, persistence, and duration by introducing dynamic properties of team interaction (Krivitsky & Handcock, 2014).

SAOM is conducted at the individual level of analysis such that individuals have agency over their own decisions and requires whole network data broken into longitudinal networks to assess change over time (Schaefer & Marcum 2017). SAOM can answer the same questions as STERGM with the added ability to assess multiple types of relations in a single model. SAOM can additionally assess questions about the impact that network structure conversely has on actor attributes. An example question SAOM can answer is, "How do individual attributes change over time based on team interactions?" Research supports that frequent interaction enhances trust (Jarvenpa et al., 1998), but suppose a researcher wanted to know *how* these interactions impact trust – specifically, how does a team's communication structure impact trust? Researchers can use SAOM to answer the question of how trust between team members changes over time based on network connections, as outlined below:

(1) Researcher collects relational data for a team over time, including edge formation and actor attributes (e.g., trust levels at each time point).
(2) Researcher breaks data into logical time periods of interest.
(3) After cleaning and formatting the data, the researcher runs a SAOM that includes effects of interest (i.e., trust levels and edge formation).
    a. In this simplified example, the model will use the behavioral function since it is the network structure that is predicted to drive changes in attribute levels.
(4) Beta values will be produced from the model for each model parameter (i.e., a linear effect, a quadratic effect, and a trust effect). These values will be used to calculate the contribution of each potential decision an actor will make (i.e., decrease trust by one, keep current trust level, increase trust by one) which will be used to determine the most probable action choice for an actor.
    a. The potential decision (options for change in trust) with the highest sum across the three effects will be selected as an agent's decision.

SAOM further facilitates the study of dynamic network phenomena. Through specification of the co-evolution of network and behavior, SAOM can examine the complex interrelations of temporal team dynamics and team member attributes simultaneously (Kalish, 2020). SAOM can assess how team member attributes impact team relations and can also identify relational mechanisms responsible for the evolution of team phenomena such as team norms and attitudes. This examination of how lower-level psychological phenomena produce interactions within teams that result in higher-level team phenomena furthers the examination of team processes.

REM is conducted at the edge level such that individual actions and relations are examined without any aggregation, which requires an ordinal or continuous series of social interaction data. REM can answer questions about the sequence, patterns, timing, and likelihood of social events. An example question REM can answer is, “What sequence of team behaviors drives what will occur next?” Specifically, suppose a researcher wanted to know what patterns of information sharing will enhance team outcomes, such as innovation. Rather than collecting data at discrete time points and assessing what aggregated behaviors produce which outcomes, REM would allow the researcher to study each sequence of communications and their resulting outcomes, as outlined below:

(1) Researcher collects relational data for a team over time and team outcomes (i.e., innovation).

(2) Researcher breaks data into logical time periods of interest, if desired.

(3) After cleaning and formatting the data, researcher runs a REM that includes relational effects hypothesized to impact innovation, such as reciprocity and high initiation (sending many relational events).

(4) REM estimates effects for each variable for each team, identifying relational tendencies within teams.

    a. For example, a high value for reciprocity for a team would indicate that the team assessed has high patterns of reciprocal exchange; a high value for high initiation would indicate that teams have members who share many ideas with other team members.

(5) While REM itself cannot directly address the how relational sequences impact outcomes, this can be accomplished by comparing the results of independent t-tests for statistics assessed between teams rated as highly innovative and lowly innovative (Pilny et al., 2016).

REM examines team process by analyzing data at the interaction level rather than aggregating data to a single time point. Interactions in REM are dependent on the situational context, individual attributes and events that transpired previously. This approach focuses on the evolution of actions over time rather than treating interactions as elements of higher-level phenomena. REM furthers the study of team process by enabling the identification of fine-grained interaction patterns amongst all possible team interactions (Pilny et al., 2016).

Study Rationale

This study utilized a network perspective and theories of team process to examine teamwork in National Basketball Association (NBA) teams to represent a descriptive foundation for future studies using theories of time to study teams and demonstrate the utility of dynamic network models. Applying a network perspective to study team process forces an interactionist perspective that incorporates individual attributes and their context to create network phenomena (Brass, 2011), which is critical for studying emergence in teams (Kozlowski et al., 2016). Taking a dynamic network approach to study team process requires fine-grained data on interaction-level behavior amongst team members. Applying STERGM, SAOM and REM to the rich data provided for NBA teams overcomes traditional challenges to studying teams to advance an understanding of team process.

This study analyzed data collected on teams in the NBA. NBA teams operate in a dynamic, ambiguous, intensive context that changes both within teams and for each game played. Within NBA teams, there are changes in team membership and team roles (i.e., player positions). For each game played, teams must change their game play location, their on-court configurations based on opponent strategy, and their game play strategy. While some changes, such as team membership, opponent, and location, are somewhat predictable, many changes experienced by NBA teams are unpredictable, requiring quick, dynamic responses to events as they occur. These nuanced, dynamic responses provide unique insight to team functioning.

NBA teams employ multiple players with varying positions and skill levels who adapt to their context and must select and rotate players throughout the course of a season and a game based on various contextual factors. When team membership (the individuals belonging to a team at any given time) changes, a team's composition changes. This continual change forces teams to frequently reset their team norms and interaction patterns and requires socialization of new team members (Feldman, 1984; Anderson & Thomas, 1996; Chen & Klimoski, 2003). When team configuration (the five individuals on the court during game play) changes, the team must collectively adapt strategies for game play.

Actions involved in NBA game play include both offensive and defensive actions. Offensive actions are taken with the goal of scoring points for a team. These actions include passing the basketball and taking field-goal shots. Defensive actions are taken with the goal of stopping an opponent team from scoring points. These actions include securing rebounds when the offensive team misses shots and forcing the offensive team to lose control of the basketball (i.e., make the offensive team commit turnovers). For a single season of game play, over one million actions and interactions are recorded that can be leveraged for studying team processes.

The processes that result in success for a single game against a single opponent will reasonably vary from processes of a different game or opponent, forcing NBA teams to adapt their processes and select different strategies depending on the nature of their context. The actions players take throughout a game are highly dependent on the actions of other players. Shots cannot be taken by a single player without being the result of an action that another player, either a team member or opponent, took. The interdependence required of NBA teams warrants a relational perspective to studying team process.

Dynamic network models can leverage the vast, detailed data captured on basketball game play in the NBA to study team processes. STERGM, REM and SAOM can examine team processes through a network lens to assess the effects that team member attributes and context have on network formation, and the effects that network formation have on team member attributes. STERGM utilizes detailed interaction sequences that can be broken into various longitudinal panels (Krivitsky & Handcock, 2014; Schaefer & Marcum, 2017). STERGM assesses temporally sensitive model terms (e.g., formation, persistence, and dissolution of edges) and the time trends responsible for changes in edges (e.g., linear, quadratic). Using NBA data, STERGM can assess the passing patterns that exist between players in a team that explain game play strategy and how these patterns change over time, providing insights to how team processes change over time.

SAOM identifies the evolution of team processes in a network that occur between observed time points (Leifeld & Cranmer, 2015). SAOM utilizes detailed interaction sequences broken into discrete time points by breaking interactions into a series of mini-steps (Kalish, 2020). These mini-steps can explain both relational (network) changes and behavioral changes that occur for a team. Using NBA data, SAOM can assess the passing patterns (e.g., reciprocity, transitivity) that occur for teams and can assess how player attributes (e.g., scoring) change based on relational behavior, exploring not only how individual behaviors impact team processes, but also, how individual behaviors *change* based on team processes.

REM represents sequential actions that comprise a process, such as team performance (Schaefer & Marcum, 2017). REM can leverage team passing sequences provided by NBA data to discover the prominence and impact of team interactions and team member attributes, such as reciprocity, transitivity, and player position. REM can additionally assess how team context, such as home versus away status for a game, impacts the actions taken by team members. To assess how these actions and interactions impact team outcomes, coupling REM with a series of independent t-tests can show how team outcomes change based on varying passing sequences, bringing research closer to understanding the manifestation of individual actions and team interactions to produce team outcomes.

Applying these dynamic network models to NBA data can advance the study of team processes by addressing key challenges to studying team process today (Leenders et al., 2016). STERGM, SAOM and REM address the challenge of using underdeveloped theories in relation to studying dynamic team phenomena by requiring an interactionist perspective coupled with a process-oriented perspective of teams. For a dynamic network analysis, it is critical to understand that different team processes are critical at different times (i.e., during different performance episodes) for team success (Marks et al., 2001). NBA data addresses this theoretical perspective through the intensive, ambiguous context faced by NBA teams regularly. By having data on team context, such as changes in team configuration and opponent strategy over time, STERGM, SAOM and REM can model these contextual effects to explain the phenomena that produce network structures (e.g., highly successful passing sequences) and behavioral changes (e.g., changes in player scoring behavior).

STERGM, SAOM, and REM address the challenges of conceptualizing process as being stable over time through aggregating data into summary indices and assuming that repeated measurements capture team dynamics by leveraging longitudinal data. These three methods use longitudinal data to assess how team processes change over time, with REM leveraging continuous relational data in its raw form. While STERGM and SAOM require some aggregation into time points, both methods can leverage continuous relational data that capture nuanced team process over time. STERGM and SAOM provide flexibility in determining appropriate time points for analysis based on theoretical considerations. In the case of NBA data, these time points can be as fine-grained as a single passing sequence to provide a detailed examination of process. By utilizing the continuous data presented by NBA teams, all three methods push research beyond descriptive insight of *what* occurs in teams to explanatory insight of *how* teams do work.

STERGM, SAOM and REM overcome the challenge of treating team member interactions as homogenous by incorporating individual differences in modeling relations over time. NBA data provides detailed information on both the actions and attributes of team members. STERGM and REM can use NBA data to assess whether and how individual attributes, such as team position and scoring behavior, impact relational patterns such as edge formation and dissolution (i.e., STERGM) and interaction sequences (i.e., REM) over time. SAOM can incrementally assess how relational dynamics subsequently impact individual differences. By leveraging nuanced NBA data, these three methods can examine heterogeneity of interactions based on individual attributes within teams that produce team outcomes.

Statement of Research Questions

This dissertation examined a series of research questions for each of the dynamic network models presented (i.e., STERGM, SAOM, and REM) to show how these models provide insight on teamwork using basketball teams from the NBA. The effects included in assessing these research questions were: (1) individual player attributes of basketball position (team role) and scoring; (2) passing behavior between all players in a team for all games played; (3) external network feature of home versus away status; (4) team outcomes of games won or lost for each team for each game played.

Table 16 shows the research questions that this dissertation addressed, the primary model effects included, and the models that were used to address each question. The first set of research questions were addressed using STERGM as STERGM is well-suited for assessing the effects of actors, edges, and covariates within networks at the dyadic level (Schaefer & Marcum 2017). The first two research questions focused on network attributes, specifically assessing the network patterns that explain relationship formation and persistence for NBA teams. Research Questions I and II were used to understand the varying levels of interconnection amongst team members over time, and assess how the factors that explain relationship formation differ from those that explain relationship persistence:

Research Question I. What network attributes explain how passing relations form within teams across a season?

Research Question II. What network attributes explain how passing relations are maintained within teams across a season?

NBA teams are comprised of players from five positions: point guards, shooting guards, small forwards, power forwards, and centers. Different positions may adopt different passing strategies as each position has at least a partially unique purpose with respect to basketball strategy. Generally, a point guard serves as the initiator of offensive play; shooting guards and small forwards attempt to score points with moderate passing responsibility; power forwards and centers work to score shots and collect rebounds. This research assessed the impact that player position had on relationship formation and persistence within teams through Research Question III:

Research Question III. What are the impacts of player position on passing behavior within teams across a season?

The second set of research questions were addressed using SAOM as SAOM is well-suited for assessing the intersection of network structure and actor attributes at the individual level (Schaefer & Marcum 2017). Research Question IV assessed a similarity effect, which examines an individual's propensity to enhance connections with those who have behavioral levels close to their own (Kalish, 2020). For this study, a scoring effect was modeled using recipient scoring (i.e., how many points players scored) and a similarity effect was modeled using scoring similarity, expressed as a player's tendency to send passes to those who score similarly:

Research Question IV. How does scoring behavior impact passing?

Research Question V leveraged a beneficial feature of SAOM, which is its ability to assess both network and behavioral effects simultaneously. SAOM provides actors agency in choosing the type of change they wish to create, which can include a change to their network (i.e., change a single outgoing edge) or a change to their behavior (i.e., change their level of a given behavior). To study these phenomena, Research Question V assessed the comparative importance of network change versus behavior change across teams within games, focusing on changing network effects of passing reciprocity and passing transitivity, and the behavioral effects of recipient scoring and scoring similarity:

Research Question V. What is the comparative importance of network versus behavior change for teams within games?

Research Questions VI, VII and VIII were assessed using REM as REM is well-suited for assessing sequencing, patterns, timing, and likelihood of relational events occurring at the edge level (Schaefer & Marcum, 2017). The edge level represents a single interaction between two actors. This model requires no aggregation, thus serving as the finest level of analysis of these dynamic network models. This research also sought to assess the analysis of similar model terms using different methods. This research modeled four REM participation shifts: (1) PSAB-BA, modeling a reciprocity effect for passing; (2) PSAB-BY, modeling continuous passing sequences amongst a set of players;

(3) PSAB-XY, modeling turn usurping in which new players take over a passing sequence; (4) PSAB-AY, modeling turn continuing in which the originator of a pass sends passes to new players. Thus, this research assessed how player scoring impacted passing sequences using REM, similar to RQIV for SAOM, through Research Question VI:

Research Question VI. How do player attributes (i.e., player scoring) impact passing sequences?

Research Question VII assessed the relationship between team context and passing behavior. For basketball teams, perhaps the most prevalent context is home or away status. Traditionally known as a “home court advantage,” home teams have the benefit of environmental familiarity, likely have traveled shorter distance prior to gameplay, signifying more rest for the team, and likely have majority of a stadium’s fans providing social support and motivation during gameplay (Mizruchi, 1985; Entine & Small, 2008; Boudreaux, Sanders, & Walia, 2017). This study examines the home court advantage effect through Research Question VII:

Research Question VII. How does team context (i.e., home versus away game status) relate to passing sequences?

Perhaps one of the most pressing questions of team process research relates to *how* team processes impact team outcomes, such as team performance (LePine et al., 2008). Due to its edge level of analysis, REM is a useful method to address this question. Research Question VIII focused on the relation between team process and team outcomes by examining what pattern of passing sequences leveraged by teams (i.e., their passing strategies) relate to optimal team outcomes (i.e., games won). An optimal team outcome is defined as whether a team won a game or lost a game. These effects were modeled in Research Question VIII:

Research Question VIII. What passing sequences used throughout a game are associated with optimal team outcomes (i.e., team wins)?

Table 16

Dissertation Research Questions

#	Research Question	Primary Model Effects	Method to Assess
I	What network attributes explain how passing relations are formed within teams across a season?	Edges, mutual, transitivity	STERGM
II	What network attributes explain how passing relations are maintained within teams across a season?	Edges, mutual, transitivity	STERGM
III	What are the impacts of player position on passing behavior within teams over time?	Edges, nodeifactor (impact of nodal covariate (position) on in-bound passes)	STERGM
IV	How does scoring behavior impact passing?	Recipient scoring, scoring similarity	SAOM
V	What is the comparative importance of network versus behavior change for teams within games?	Reciprocity, transitivity, recipient scoring, scoring similarity	SAOM
VI	How do player attributes (i.e., player scoring) impact passing sequences?	Covariate effect for scoring	REM
VII	How does team context (i.e., home versus away game status) relate to passing sequences?*	Covariate effect for scoring, PSAB-BA, PSAB-BY, PSAB-XY, and PSAB-AY	REM

VIII	What passing sequences used throughout a game are associated with optimal team outcomes (i.e., team wins)?*	Covariate effect for scoring, PSAB-BA, PSAB-BY, PSAB-XY, and PSAB-AY	REM

**Note:* Additional analyses required to assess full research question. To assess the impact of team context (i.e., home versus away) on passing sequence, a Multivariate Analysis of Variance (MANOVA) was conducted. To assess the impact of passing sequence on team outcomes (i.e., wins versus losses), a logistic regression was conducted. For more details, see “Analyses” section.

Method

Data Collection

A large data collection effort was organized to record basketball passing and action sequences by the 30 teams playing in the National Basketball Association (NBA) for all 1,309 games played in the 2016-2017 season. Games throughout the season were manually coded by more than 70 graduate and undergraduate students at a midwestern university and other coders. The manual coding involved coders watching basketball games online and recording passes and actions by players. The recruiting effort for coders began in the fall of 2016 and continued through the end of 2017. The recruiting effort involved creating and posting flyers around campus and advertising to students in classrooms about the research opportunity. Coders were taken through a training designed to orient them to the fundamentals of basketball game play and were trained on the critical actions and passes to be recorded. The initial coding effort took more than 18 months (i.e., fall 2016 into 2018) and 4,000 coding hours, while evaluation of coded games for accuracy took approximately 2 years.

Coders were trained on how to code actions and passing sequences (detailed in *Data Description*). Coders worked closely with researchers on how to code games and coded their first few games with a partner – where one individual was watching the game and identifying the actions, and the other was tracking the actions in the coding template.

A coding template was provided to each coder that broke coding actions into possession number, the team that had possession at a given time, and the passing sequence itself. Researchers would review the work of the coders during their initial coding phase and determine when coders were ready to code independently. At this point, coders were responsible for watching the game and capturing each action into the coding spreadsheet. Researchers would periodically spot-check the quality of the coding throughout the coding process and work with coders to resolve any issues in coding.

Player and team data were scraped from Basketball-Reference (www.basketball-reference.com) for players in the 2016-2017 NBA season to obtain information on player position (i.e., point guard, shooting guard, small forward, power forward, and center) to answer research questions focusing on nodal attributes. Team data includes home versus away status for each game and wins/losses which provided information in answering research questions focusing on the impact of team context and outcomes.

Data Description

This study utilized manually coded basketball passing data and publicly available data from the 2016-2017 NBA season. A total of 1,309 games were played in the 2016-2017 NBA reason. Specifically, the data consists of passes completed and actions taken by players for each team within a single game across an entire season, resulting in approximately 1.2 million recorded actions. These actions include offensive and defensive actions, as well as passes between players.

Table 17 shows key actions and their related codes used in data collection for recording actions during a possession. This list represents all possible actions that players can take throughout the course of a game. Offensive actions include field goals, free throws, and offensive rebounds. Field goals are any shot scored by players that is not a free throw. There are two types of field goals: two-point field goals and three-point field goals. Three-point field goals are taken from outside of the arc on a court, and two-point field goals are taken from inside of the arc. There are two possible outcomes for field goals: attempted and made. Attempted field goals are unsuccessful shots and are denoted in this study as "FGA-" (field goal attempt). Made field goals are successful shots and are denoted in this study as "FGM-" (field goal made). The hyphen following "FGA" or FGM" represents the type of field goal: two-point or three-point. Two-point field goals will be followed with a "2," and three-point field goals will be followed with a "3." Shots that are taken because of a team committing a foul, or the illegal personal contact a player makes, are known as free throws. Free throws are classified as "FTM-" where the hyphen represents the number of successful free throws, which can range from zero to three. Offensive rebounds occur when the offensive team secures a rebound and maintains possession of the ball. Offensive rebounds are denoted as "ORB."

Defensive actions include turnovers and defensive rebounds. There are two types of turnovers that can occur: live ball turnovers and dead ball turnovers. A live ball turnover, also known as a "steal," occurs when the defensive team secures the ball from the offensive team without stopping the clock (e.g., without the ball going out of bounds or committing a foul). Live ball turnovers are denoted as "LBT." A dead ball turnover occurs when the offensive team touches the ball out of bounds or commits an offensive foul, thus turning possession over to the defensive team. This is referred to as a "DBT." The final defensive action is a defensive rebound, or a "DRB," which occurs when the defensive team secures a rebound from a shot taken by the offensive team, shifting possession from the offensive to the defensive team.

Other actions not directly related to specific offensive or defensive actions include the ball going out of bounds, a jump ball, a live ball, a personal foul, a technical foul, a flagrant foul, and a time out. Out of bounds, or “OB” occurs when the defensive team hits the ball out of bounds during an offensive team’s possession. A jump ball, or “JB,” always occurs at the start of the game to determine who has first possession and can occur at other points throughout the game if it is unclear who should have possession of the ball. A loose ball, or “LB,” occurs when the offensive team loses control of the ball, and both teams are fighting to secure a possession. Fouls can occur at any point in a game and can be classified as one of three types: personal fouls, technical fouls, and flagrant fouls. Personal fouls (“PF”) are the least severe of the three and occur whenever a player commits a violation on an opposing player that limits a player’s ability to move, score, or perform an action. Technical fouls (“TF”) occur when there is no physical contact between players, but rather unsportsmanlike conduct occurs. Flagrant fouls (FF) occur when there is excessive or violent contact by a player that could result in injury for the player being fouled. There are two types of flagrant fouls: Flagrant 1 (“FF1”) is a foul that is considered unnecessary, and Flagrant 2 (“FF2”) is an unnecessary foul that includes excessive force. FF2 results in the player who committed the foul to be ejected from the game entirely.

Data were also collected on the passing actions taken by players. *Table 18* provides a sample sequence recorded from a game played between the Golden State

Table 17

Key Action Codes for Recording Actions During a Possession

Action Type	Action Code	Action Description
Offensive	FGA2	Two-point field goal attempt missed
	FGM2	Two-point field goal made
	FGA3	Three-point field goal attempt missed
	FGM3	Three-point field goal made
	FTM	Free throws made (followed by the number of successful free throws)
	ORB	Offensive rebound
Defensive	DBT	Dead ball turnover (change of possession from: ball out of bounds on offensive team, offensive foul, offensive lane violation)
	LBT	Live ball turnover
	DRB	Defensive rebound
Other	OB	Out of bounds, same team possession
	JB	Jump Ball
	LB	Loose Ball
	PF	Personal Foul
	TF	Technical Foul
	FF	Flagrant Foul (followed by a one or a two to represent FF type; FF1= player who committed the FF remains in game; FF2 = player who committed the FF is rejected from game)
	TO	Time out

Warriors (GSW) and the Los Angeles Clippers (LAC) to highlight the nuanced level of detail captured through this data recording process. The data set is organized into three columns: (1) possession number; (2) team with possession of the ball; (3) possession sequence, which includes who passed to whom (with numbers representing player jersey numbers) and the actions taken by each player. For example, possession #1 tells us the following: (1) for the first possession of the game, (2) the Golden State Warriors took the following actions: (3) player #30 passed to player #11, who passed to payer #27, to #35, to #30, back to #27, to #35 who attempted a two-point field goal (FGA2) in which the opposing team had a defensive rebound (DRB). This level of detail provides insights into basketball teamwork rather than solely using the sum and average number of actions taken by players on a team.

Table 18

Sample Sequence of Five Possessions From GSW-LAC

Possession	Team	Possession Sequence
1	GSW	30-11-27-35-30-27-35-FGA2-DRB
2	LAC	25-12-FGA2-ORB-OB-32-25-32-FTM1
3	GSW	23-FGA2-ORB-30-FGM2
4	LAC	25-6-32-25-FGA3-DRB
5	GSW	35-FTM2

The intricate detail of what occurs, for example, between GSW's #30 and the defensive rebound (DRB) that concludes their possession provides a partial movie of game play: GSW's strategy for their first possession was to move the ball around the court by passing to four out of five of their total players on the court that eventually resulted in a failed shot. However, in their second possession (possession #3 in *Table 18*), only two players possessed the ball, and although the first part of the possession resulted in a failed shot, the second part of the possession following the offensive rebound (ORB) resulted in a successful shot. The differences in these sequences represent the variety of game play by teams, providing an opportunity for teams to evaluate the success of their game play strategies and adapt their strategies accordingly.

Data Vetting

The data were vetted to assess the quality of manually coded data. The vetting process was as follows:

(1) Created a list of "permissible codes", which includes true action codes that could be recorded during a game, and the player numbers for all active

members of the 2016-2017 NBA season. Permissible codes include all actions listed in *Table 17*, plus "EOQ" representing the end of a quarter, and the following jersey numbers representing active players in the 2016-2017 NBA season: 00, 0-51, 54-55, 77, 88, 90-92, 95, and 99.

(2) Extracted all action codes and player numbers that were not in the list of permissible codes, along with the action/player number, game number, and team name.

(3) Identified abnormal patterns that existed in sequences, such as a "DRB" (defensive rebound) occurring in the middle of a sequence rather than at the end (DRB is a code that concludes a possession, therefore it can only exist if it is the final action at end of a sequence).

(4) For each extracted item or abnormal pattern identified, video clips were watched of the original games to recover the true actions/player numbers responsible for actions and the passing sequences were updated to reflect true actions. *Figure 15* represents an example of transforming a non-permissible action recorded for a game.

A total of 1,267,824 total codes, including both player passing and actions, constitute the 2016-2017 season across the 1,309 games. The data vetting process was concluded when there was a sufficient match between game-level statistics computed from the manually coded sequences and official NBA box score statistics. A sufficient match was assessed using total field goal attempts (FGA; both two-point and three-point shots) taken by players in each game. A mismatch between manually coded and NBA recorded field goal attempts were assigned to one of four categories: 0 incorrectly coded

Figure 15

Replacing Non-Permissible Code Process

(1) Identify non-permissible code

Possession #	Team	Possession Sequence
1	GSW	30-11-27-FGA2-DRB-35-30-27-FGM2
2	LAC	25-12-FGA2-ORB-OB-32-25-32-FTM1
3	GSW	23-FGA2-ORB-30-FGM2
4	LAC	25-6-32-25-FGA3-DRB
5	GSW	35-FTM2

(2) Identify team and possession number as a starting point for reviewing actions that occurred in the game on video

Possession #	Team	Possession Sequence
1	GSW	30-11-27-FGA2-DRB-35-30-27-FGM2

(3) Review the video that captures the non-permissible action and identify the correct action; replace the incorrect action with the correct action

Possession #	Team	Possession Sequence
1	GSW	30-11-27-FGA2-ORB-35-30-27-FGM2

Figure 15. Example identification and transformation of non-permissible action codes.

FGAs, 1-5 incorrectly coded FGAs, 6-10 incorrectly coded FGAs, and 11-15 incorrectly coded FGAs, with 15 incorrectly coded FGAs in a single game serving as the maximum allowance of mismatch. Data vetting was complete when all of the manually coded games had less than 16 FGAs incorrect relative to the NBA recorded data. Of the coding categories, approximately 11% of games had 0 incorrectly coded FGAs, 67% of games had 1-5 incorrectly coded FGAs, 17% of games had 6-10 incorrectly coded FGAs, and 4% of games had 11-15 incorrectly coded FGAs.

Data Transformation

The possession sequences for each team for each game required transformation into edge lists for two of the analytical methods (STERGM, SAOM), which creates a row for each dyadic connection between two individuals. This transformation and all other analyses were completed using *R* (R Core Team, 2019) via *RStudio* (RStudio Team, 2016) using the following packages: "tidyverse," which includes "ggplot2," "dplyr," "tidyr," "readr," "purr," "tibble," "stringr," (Wickham, Averick, Bryan, Chang, McGowan, François, Grolemund, Hayes, Henry, Hester, Kuhn, Pedersen, Miller, Bache, Müller, Ooms, Robinson, Seidel, Spinu, Takahashi, Vaughan, Wilke, Woo, & Yutani, 2019); "sna" (Butts, 2020); "dils" (Honaker, King, & Blackwell, 2011); "psych" (Revelle, 2020); "qgraph" (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012); "tidygraph" (Pedersen, 2020); "rem" (Brandenberger, 2018); "relevent" (Butts, 2015); "statnet" (Handcock et al., 2018); "RSiena" (Ripley et al., 2021); "rvest" (Wickham, 2020). *Figure 16* provides an overview of the data transformation process from raw data to edge lists. The edge list transformation process is as follows, using a single game as an example:

(1) Starting with the first possession of a game, split the possession sequence into each individual action.

(2) Iterating over the length of total actions within a possession, extract the player actions taken that are *not* passes.

(3) For each team, split the sender-receiver actions into two columns using the hyphen between players (representing *passes*) into a new data frame: "Sender" and "Receiver," respectively. The new data frame represents an edge list such that for each action taken, there is a sender of a pass and a receiver of a pass.

Figure 16

Transformation from Raw Data to Edge List

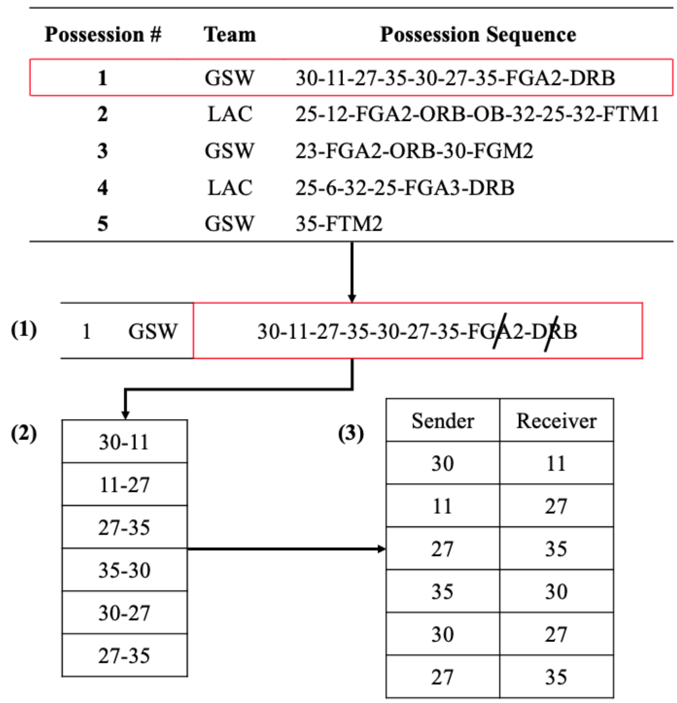


Figure 16. Example transformation from GSW first possession in raw data form into Sender-Receiver edge list. Sequences are transformed one at a time, extracting passing information and splitting individual passes into dyadic Sender-Receiver observations.

This process iterated over all 1,309 games in the 2016-2017 NBA season. There is an edge list for each quarter played in each game for each team, resulting over 10,000 individual edge lists for analysis (2,618 dynamic edge lists, with each dynamic edge list for each game/team combination being comprised of one edge list per quarter). For REM analyses, the data remained in their raw form, with each pass ordered sequentially. The sequential time stamps are ordinal as there is not a continuous indicator of the time of passes.

STERGM and SAOM required further transformation. These two methods require transforming edge lists into adjacency matrices, which consists of a graph with rows and columns representing network actors. STERGM uses weighted connections, requiring an edge list with total connections between two individuals. SAOM requires an edge list representing only the existence (represented by a 1) or non-existence (represented by a 0) of a connection. The transformation process involves extracting individual sender-receiver relationships for both STERGM and SAOM and summing them for each dyad in STERGM (i.e., number of total connections between any two individuals). The extracted edges are placed into the cells of a square adjacency matrix, with rows representing senders, and columns representing recipients. *Figure 17* shows an example transformation of an edge list to an adjacency matrix for weighted connections in STERGM. For SAOM, cells would only receive values for existence (1) or non-existence (0) of a connection.

Figure 17

Example Transformation from Edge List to Adjacency Matrix

Sender	Receiver
30	11
11	27
27	35
35	30
30	27
27	35

↓

Receiver

Sender		**30**	**11**	**27**	**35**	
	30	0	1	1	0	30 passes to 11 and 27 once
	11	0	0	1	0	11 passes to 27 once
	27	0	0	0	2	27 passes to 35 twice
	35	1	0	0	0	35 passes to 30 once

Figure 17. Example transformation from GSW first possession Sender-Receiver edge list into Sender-Receiver adjacency matrix. The adjacency matrix for STERGM totals the number of passes between Sender-Receiver dyads to create a weighted matrix.

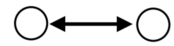
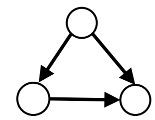
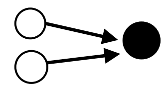
Both STERGM and SAOM require aggregating these data into time points. This dissertation aggregated data for STERGM and SAOM into quarters, given quarters represent natural breaks in game play. As a result, each quarter within a game for a single team represented a passing network. Time-based analyses were conducted across an entire game for a single team, assessing network and behavioral patterns that occur throughout a single game.

Results

To analyze the Research Questions I-III (RQ I: What network attributes explain how passing relations form within teams across a season? RQ II: What network attributes explain how passing relations are maintained within teams across a season? RQ III: What are the impacts of player position on passing behavior within teams across a season?), STERGM was applied via the *statnet* package (Handcock et al., 2018). STERGM requires specifying network predictions, similar to a regression equation, where the dependent variable is the network and the independent variables are the proposed network effects. Weighted networks were used to conduct STERGM analyses in this dissertation. For Research Questions I-III, two models were specified. Model 1 included an *edges* term (to control for overall network density), a *mutual* term (reciprocity), and a *transitive* term (assessing triangles in a network) to answer RQs I and II. Model 2 included an *edges* term and a nodal covariate, *nodeifactor*, to answer RQ III. *Nodeifactor* assesses the impact a factor (in this analysis, player position) has on receiving connections (i.e., passes). *Table 19* provides a visual for each of the terms used.

Table 19

Model 1 and Model 2 Network Attributes

Effect	Model Term	Description	Visual
Reciprocity	*Mutual* (referred to as mutual ties)	Probability of an edge forming increases if it closes a mutual pair	
Transitivity	*Transitiveties* (referred to as transitive ties)	Probability of an edge forming increases if it closes a triad	
Shared nodal attribute	*nodeifactor.Position.x** (referred to as position)	Probability of an edge forming increases based on positional attribute	

*Note: The referent position is Center and x = one of four positions: shooting guard (SG), point guard (PG), small forward (SF) or power forward (PF).

STERGM requires defining appropriate time periods for data aggregation. Given STERGM requires panel network data, and basketball quarters create natural breaks in game play, each game was broken into quarters and transformed into quarter-networks by team, resulting in 2,618 dynamic networks with anywhere between four and six networks for each game (for each quarter played, resulting in over 10,000 individual networks for analysis). *Figures 18-21* show four networks from two games where the Golden State Warriors (GSW; the best NBA team in the 2016-2017 season) played against the New York Knicks (NYK; the worst NBA team in the 2016-2017 season) to show variance in strategies adopted by teams.

Figure 18

NYK Game 1 Against GSW

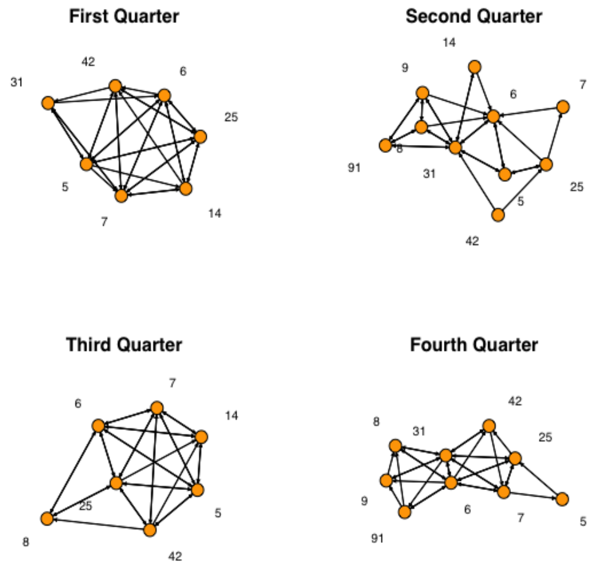


Figure 19

GSW Game 1 Against NYK

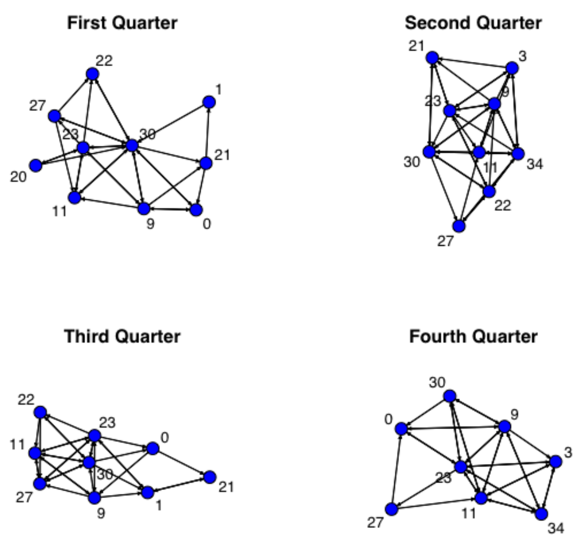


Figure 20

NYK Game 2 Against GSW

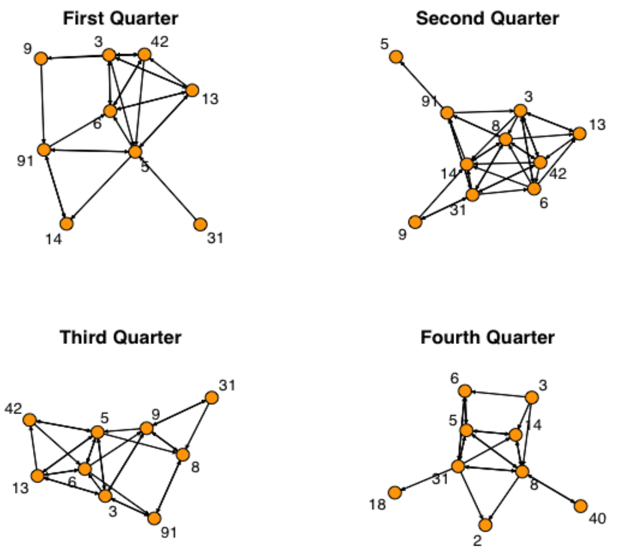
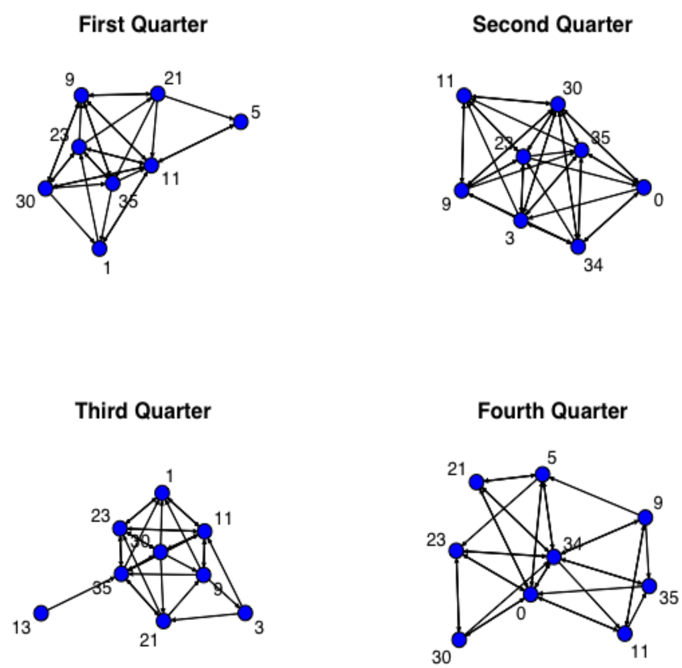


Figure 21

GSW Game 2 Against NYK



STERGM models use conditional maximum likelihood estimation (CMLE) to estimate model terms given the data are network panel data without duration information (Statnet Development Team, 2021). Model 1 was used to assess RQs I and II given it included network attributes (as opposed to nodal attributes). *Table 20* shows output from Model 1 for the two sample games (NYK vs GSW). In the first game played between NYK and GSW, the mutual tie formation (*Form~Mutual Ties*) coefficient for NYK is positive (b = 2.10), indicating there is an 89% chance a relation will form between players during the game if it closes a mutual pair. The mutual tie formation coefficient for GSW is also positive (b = 2.20), indicating there is a 90% chance a relation will form between players during the game if it closes a mutual pair. The transitive tie formation (*Form~Transitive Ties*) coefficient is positive for both NYK and GSW; however, there is a higher chance a relation will form between players during the game if it closes a triangle for NYK (86% chance; b = 1.83) compared to GSW (65% chance; b = 0.63). The positive mutual tie persistence (*Persist~Mutual Ties*) coefficients indicate there is an 84% chance for NYK (b = 1.64) and a 72% (b = 0.93) chance for GSW that a relation will persist (i.e., be maintained) over time when it closes a mutual pair. Lastly, the positive transitive tie persistence (*Persist~Mutual Ties*) coefficients indicate there is a 64% chance for NYK (b = 0.57) and a 77% chance for GSW (b = 1.23) that a relation will persist over time when it closes a triangle.

Table 20

STERGM Results for NYK vs GSW

	NYK 1	**GSW 1**	**NYK 2**	**GSW 2**
Form~Edges	-3.93 (0.78)***	-3.10 (0.31)***	-3.62 (0.31)***	-3.36 (0.39)***

	NYK 1	GSW 1	NYK 2	GSW 2
Form~Mutual Ties	2.10 (0.42)***	2.20 (0.39)***	1.54 (0.36)***	1.69 (0.34)***
Form~Transitive Ties	1.83 (0.75)*	0.63 (0.29)*	1.21 (0.29)***	1.24 (0.37)***
Persist~Edges	-1.82 (0.30)***	-2.02 (0.29)***	-1.96 (0.31)***	-2.95 (0.38)***
Persist~Mutual Ties	1.64 (0.62)**	0.93 (0.63)	1.82 (0.73)*	1.60 (0.76)*
Persist~Transitive Ties	0.57 (0.26)*	1.23 (0.30)***	0.82 (0.30)**	1.74 (0.43)***
Iterations	8	9	14	15
AIC	364.67	436.57	434.86	435.93
BIC	387.98	462.18	461.48	461.54

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

For the second game played between NYK and GSW, the mutual tie formation coefficients indicate there is an 82% chance for NYK (b = 1.54) and an 84% chance for GSW (b = 1.69) that a relation will form between players during the game it closes a mutual pair. The transitive tie formation coefficients indicate there is a 77% chance for NYK (b = 1.21) and a 78% chance for GSW (b = 1.24) that a relation will form if it closes a triangle. The mutual tie persistence coefficients indicate there is an 86% chance for NYK (b = 1.82) and an 83% chance for GSW (b = 1.60) that a relation will persist if it closes a mutual pair. Lastly, the transitive tie persistence coefficients indicate there is a 69% chance for NYK (b = 0.82) and an 85% chance for GSW (b = 1.74) that a relation will persist if it closes a triangle.

These results suggest in the first game played between NYK and GSW, similar passing strategies were used by players in different teams. However, NYK was more likely to use passing between three individuals (transitive ties) as a strategy at some point during game play relative to GSW (formation), whereas GSW was more likely to use transitive passing as a consistent strategy quarter to quarter relative to NYK (persistence). The key difference here is between the formation and persistence of transitive passes: NYK was more likely to use transitive passing *at some point during game play* (formation) whereas GSW was more likely to use transitive passing *throughout game play* (persistence). When time is considered, a difference in transitive strategies between the two teams emerged. GSW was more likely to use transitive passes across time in their second game against NYK as well. Considering GSW won both games played against NYK (by 7 points in Game 1 and 13 points in Game 2), leveraging transitive passing strategies may be a viable strategy for positive team outcomes.

To address RQs I-II, model coefficients from Model 1 for all 2,618 dynamic network models were plotted over a season (shown in *Figure 22*). In general, these teams demonstrate similar patterns across the season assessed, with mutual tie formation emerging as the network attribute with the highest probability across the season (M = 0.83, SD = 0.07), followed by mutual tie persistence (M = 0.77, SD = 0.16), transitive tie formation (M = 0.67, SD = 0.09), and transitive tie persistence (M = 0.66, SD = 0.14), as shown in *Table 21*. Moreover, the edges terms for both the formation (M = 0.05) and persistence (M = 0.16) models are much lower than the mutual and transitive tie terms in Model 1, which highlights the increased importance of mutual and transitive passing relations relative to general passing behavior. This suggests that passing relations are likely more strategic than sending passes at random, and that a dominant player (e.g., a point guide) simply passing to other players is not a sufficiently effective strategy of gameplay.

Figure 22

Model 1 Edge Probabilities by Team Across a Season

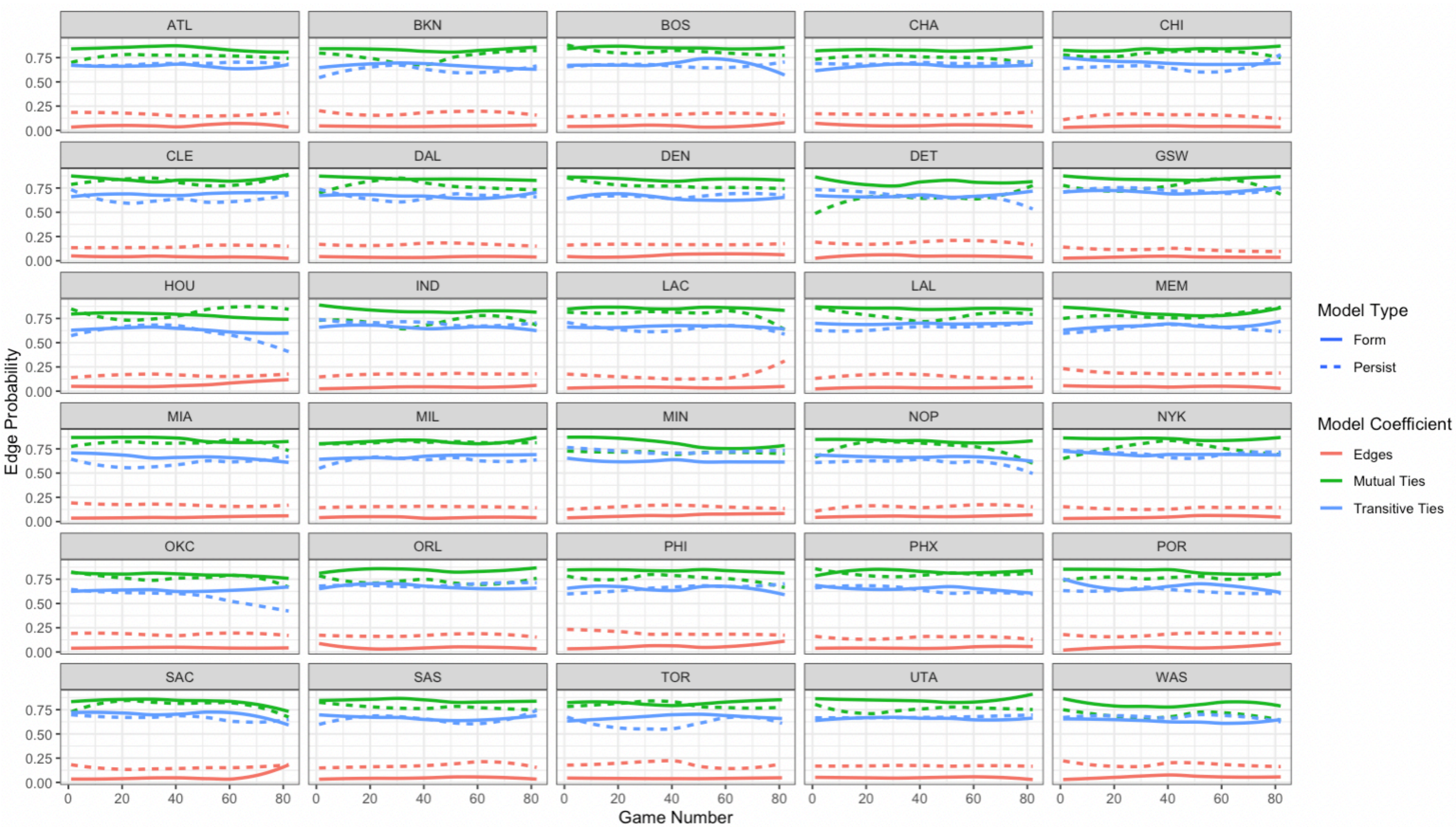


Figure 22. Coefficients from Model 1, which includes edges, mutual and transitive ties for both tie formation and persistence, are plotted for each team across the 2016-2017 NBA season by game number. Model coefficients have been transformed to represent edge probabilities for simplified interpretation. Solid lines represent formation coefficients; dotted lines represent persistence coefficients.

Figure 23 visualizes the proportion of game/team combinations that meet five probability thresholds (i.e., 50%, 60%, 70%, 80% and 90%) across the season to further examine prominent model terms. Game/team combinations represent a single game played by a single team. For example, one game/team combination is GSW's first game played, and GSW will have a game/team combination for every other game they play. Each team will have a game/team combination for each game they played during the regular season, resulting in 2,618 total game/team combinations. While more than 80% of the game/team combinations (i.e., dynamic networks) analyzed had network patterns likely explained by all four analytical model terms (*Form~Mutual Ties, Form~Transitive Ties, Persist~Mutual Ties, Persist~Transitive Ties*), the prevalence of certain model terms decreases with stricter probability thresholds. Terms for mutual tie formation generally remain the most prominent for all game/team combinations, with 95% of observed networks producing coefficient probabilities greater than 0.70. Terms for mutual tie persistence follow a similar pattern, with 75% of networks observed producing coefficients greater than 0.70. Only 36% and 39% of networks produced coefficients greater than 0.70 for the formation and persistence of transitive ties, respectively, suggesting these strategies are less common across teams throughout a season.

Table 21

STERGM Output Descriptive Statistics

Coefficient	**M**	**SD**	**Median**
Form~Edges	0.05	0.04	0.04
Form~Mutual Ties	0.83	0.07	0.84
Form~Transitive Ties	0.67	0.09	0.67
Persist~Edges	0.16	0.06	0.16
Persist~Mutual Ties	0.77	0.16	0.81

Persist~Transitive Ties	0.67	0.15	0.68

These results suggest that when assessing network attributes for all 30 teams across all games played, teams are highly likely to use forming and maintaining mutual passing relations as a strategy during gameplay. As evidenced in *Figure 22*, there is a small amount of variation across teams across the season for the network attribute coefficients assessed. In an attempt to parse out nuanced differences amongst teams for network attribute coefficients, a hierarchical cluster analysis was conducted. Cluster analyses are used to reduce a large set of observations into homogenous groups (Beckstead, 2002). Hierarchical cluster analysis is particularly well suited when the number of groups for clustering is unknown a priori. Conducting a hierarchical cluster analysis requires creating a dissimilarity matrix, which assesses the *distance* between each data point based on Euclidean distance, or the square root of square discrepancies between two data points summed over all features measured (Beckstead, 2002). For each team, data were arranged by game number (82 total games) and model coefficient (3 total coeffects – *Edges*, *Mutual Ties, Transitive Ties*) for both the formation and persistence models (2 total models) to assess if similar season-wide strategies were deployed by teams, resulting in a 30 by 492 matrix (30 teams x 82 games x 6 model coefficients) for the cluster analysis.

The method used to generate clusters was Ward's (1963) which deploys a sum of squares method to minimize the distance to the center of a cluster within clusters and maximize the distance to the center between clusters. The distances obtained were centered to ensure data were internally consistent to enable adequate comparison. *Fi*gure

Figure 23

Model 1 Game/Team Combinations and Probability Thresholds

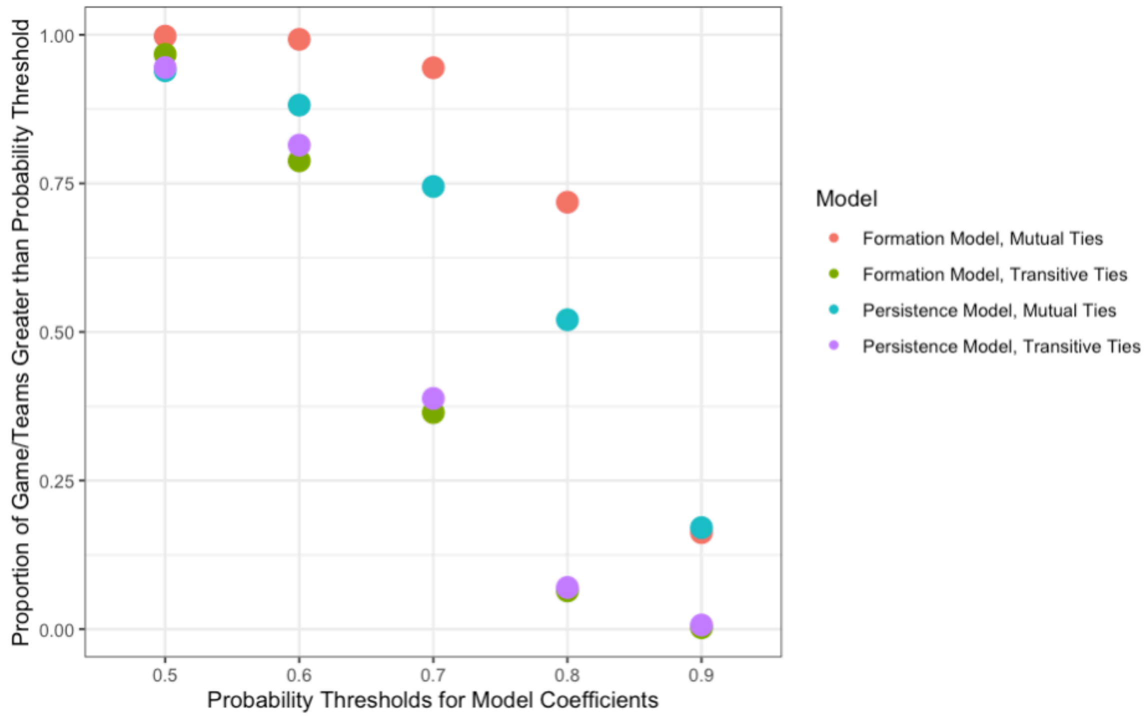


Figure 23. Figure 23 includes five probability thresholds to demonstrate the proportion of game/team network combinations that meet each threshold. For example, 100% of game/team combinations reached at least 50% probability for mutual tie formation coefficients, suggesting each team has at least a 50% chance of mutual ties forming at some point during game play.

24 shows a scree plot of the distances between clusters based on the number of groups used for analysis, which demonstrates the smaller distance between clusters as the number of clusters increases. There is no formal stopping criterion for hierarchical cluster analysis as it is designed to be an exploratory method to make sense of data (Bratchell, 1989). Typically, the elbow of a scree plot can be used to select the optimal number of clusters. However, given the minimal differences across teams across a season, the scree plot “elbows” in more than one place, specifically at both two and four clusters. If two clusters were chosen, there would be one cluster of two teams, and a second cluster of 28 teams. If four clusters were chosen, there would be two clusters of a single team, one cluster of six teams and one cluster of 20 teams. Given the exploratory nature of this research and the disproportionate clusters if only two or four groups were selected, three clusters were selected for further examination.

Figure 24

Scree Plot for STERGM Model 1 Hierarchical Clustering

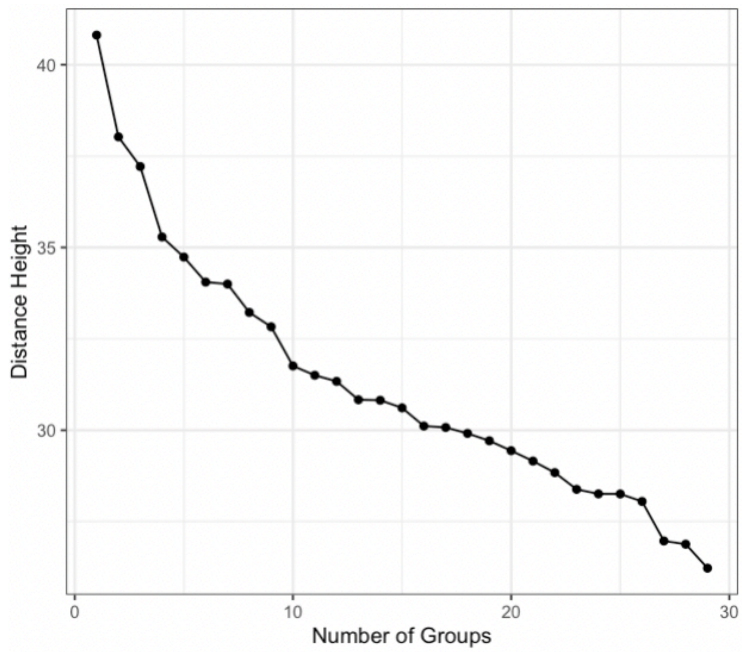


Figure 24. Scree plot demonstrating the decline in distance between clusters as the number of clusters selected increases.

The dendrogram in *Figure 25* summarizes the clustering output and visualizes the three clusters selected based on all 30 teams. Cluster 1 contains 22 teams (CHA, DEN, DAL, MIA, BKN, LAL, ATL, SAS, IND, ORL, UTA, MIL, PHX, BOS, NYK, CHI, GSW, SAC, CLE, LAC, NOP, TOR), Cluster 2 contains six teams (DET, MIN, OKC, PHI, MEM, POR) and Cluster 3 contains two teams (HOU, WAS). Descriptive statistics for each cluster are shown in *Table 22*. Generally, data in *Table 22* suggest that across the entire season (82 games), network patterns present in Cluster 1 are more likely explained by the formation of mutual ties (*M* = 0.84, *SD* = 0.06) relative to Cluster 2 (*M*= 0.82, *SD* = 0.07) and Cluster 3 (*M* = 0.79*, SD*= 0.07).

Figure 25

Dendrogram of Model 1 Cluster Analysis for All Teams

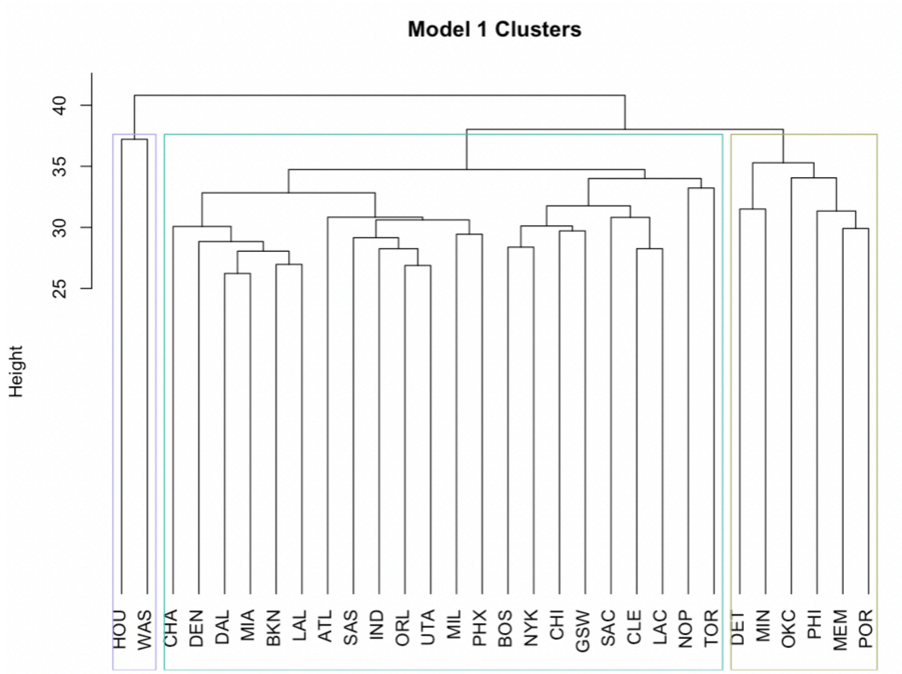


Figure 25. Dendrogram from Model 1 hierarchical cluster analysis showing the three selected clusters.

Table 22

TERGM Model 1 Cluster Descriptive Statistics

		Cluster 1		Cluster 2		Cluster 3	
Model	**Coefficient**	***M***	***SD***	***M***	***SD***	***M***	***SD***
Form	Edges	0.05	0.05	0.05	0.03	0.06	0.03
Form	Mutual Ties	0.84	0.06	0.82	0.07	0.79	0.07
Form	Transitive Ties	0.67	0.09	0.66	0.08	0.63	0.06
Persist	Edges	0.16	0.05	0.18	0.05	0.17	0.05
Persist	Mutual Ties	0.78	0.15	0.74	0.15	0.75	0.14
Persist	Transitive Ties	0.66	0.13	0.65	0.12	0.64	0.14

A similar pattern is observed for the persistence of mutual relations, such that network patterns in Cluster 1 are more likely explained by the persistence of mutual ties ($M = 0.78$, $SD = 0.15$) relative to Cluster 2 ($M = 0.74$, $SD = 0.15$) and Cluster 3 ($M = 0.75$, $SD = 0.14$). Although differences are slight, network patterns present in Cluster 1 are also more likely explained by the formation of transitive ties ($M = 0.67$, $SD = 0.09$) relative to Cluster 2 ($M = 0.66$, $SD = 0.08$) and Cluster 3 ($M = 0.63$, $SD = 0.06$), and the persistence of transitive ties ($M = 0.66$, $SD = 0.13$) relative to Cluster 2 ($M = 0.65$, $SD = 0.12$) and Cluster 3 ($M = 0.64$, $SD = 0.14$). In short, all four key model coefficients (i.e., mutual and transitive formation and persistence) are strongest in Cluster 1 relative to Cluster 2 and Cluster 3.

Whereas *Table 22* provides an assessment of the three Clusters at an aggregate level across the entire season, *Figure 26* visualizes how model coefficients change over time for teams in each cluster from game to game to further understand similarities and differences amongst the observed clusters. Teams in Cluster 2 use similar transitive passing strategies to Cluster 1 with Cluster 1 experiencing slightly less deviance in mutual formation probabilities across a season. For teams in Cluster 1, the probability of forming mutual passing relations is consistently above 80% whereas this value drops close to 80% towards the latter half of the season for teams in Cluster 2. Cluster 3 had more variability in passing strategies across the season, although the variance is likely attributable to the fact that Cluster 3 only contains two teams. The shared passing strategies of the two teams in Cluster 3 include a reliance on mutual passing formation and persistence, with the persistence of mutual passes increasing mid-season to nearly the same probability of mutual passing formation. This suggests that throughout the season, using mutual passing as a strategy for the full duration of a game (i.e., persistence) became a more likely explanation of observed passing relations towards the latter half of the season.

Figure 26

Average Coefficient Probabilities for TERGM Model 1 Clusters

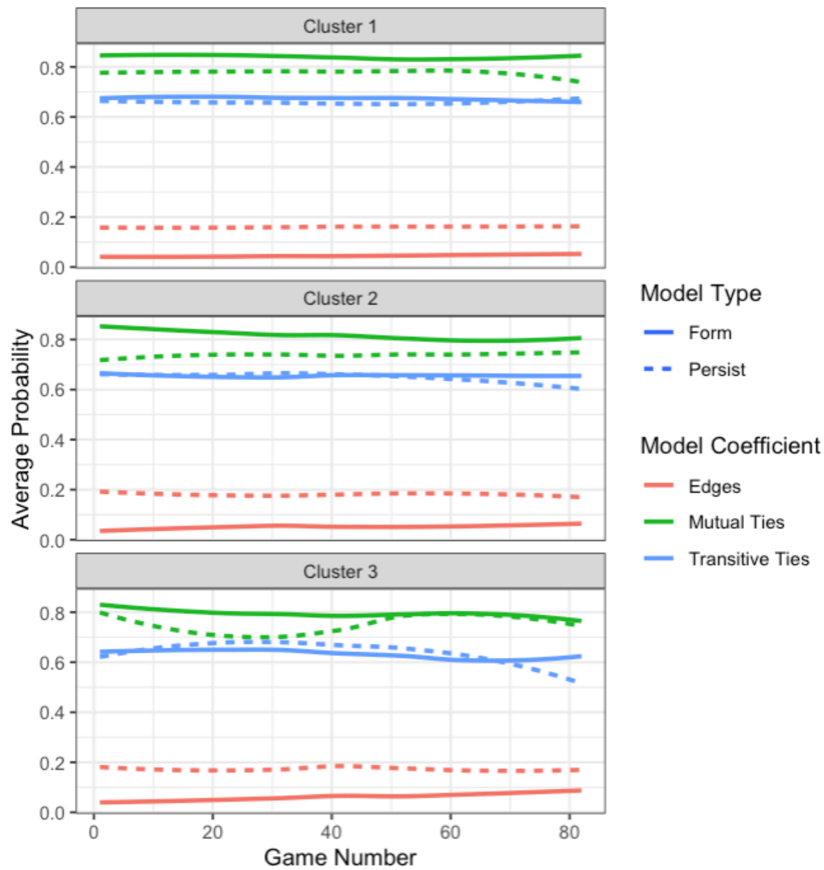


Figure 26. Average model coefficient probabilities across a season for teams by cluster. Solid lines represent formation terms, and dotted lines represent persistence terms.

One potential explanation of this is that trust amongst dyads on the team may have increased over time, or that mutual passing proved to be a more viable strategy for successful team outcomes. The persistence of transitive ties quarter to quarter for Cluster 3 were highest early- to mid-season, with average probabilities reaching 70% around game 30, then declining for the remainder of the season. A potential explanation for the observed pattern for teams in Cluster 3 could be that persistent transitive passing strategies were not yielding targeted outcomes, and that as increased pressure for playoffs approached towards the latter half of the season, a shift in strategy was needed.

However, the differences across the season for games and teams are quite small, suggesting there are not strong differences between teams across clusters. Networks for teams in all three clusters can be explained by the formation and persistence of mutual and transitive ties to a similar degree. This hierarchical cluster analysis was intended to detect nuanced similarities and differences between teams for the observed games. It appears that regardless of team or game played, basketball teams need both two-way and three-way passing patterns to be effective. While two-way and three-way passing patterns may emerge in different ways for different teams, this analysis is not sufficiently granular to highlight exact differences between these teams.

Research Question I and *II* were posed to assess what network attributes explain how passing relations form and persist within teams across a season. Given the mutual term for the formation model is highly probable across teams across the full season (with 99% of game-team combinations across the season resulting in probabilities at or greater than 60%, and 95% of networks resulting in probabilities at or greater than 70%), the formation of mutual ties is highly likely to explain how passing relations formed within teams throughout games played in the 2016-2017 NBA season. The persistence of mutual ties highly probable across teams (with 88% of networks resulting in probabilities at or greater than 60%, and 75% of networks resulting in probabilities greater than 70%).

Transitive terms also emerged as strong explanatory factors in the observed networks, although to a lesser degree than mutual terms. 79% of networks resulted in probabilities at or greater than 60% for the formation of transitive ties (with the proportion of games reaching 70% probability dropping to 36%). A similar pattern is observed for the persistence of transitive ties such that 81% of networks observed resulted in probabilities at or greater than 60% (dropping to 39% of games that reached 70% probability). Overall, these results suggest (*RQI*) that the formation of both mutual and transitive passing relations explain the observed networks, with mutual passing relation formation emerging as the most likely explanation for network patterns across the teams observed. Similarly, they also suggest that (*RQII*) the persistence of mutual and transitive passing relations explain the observed networks, with the persistence of mutual relations being a stronger explanation for relationship persistence over time relative to the persistence of transitive passing. The formation terms emerging as having stronger probabilities relative to the persistence terms (for both mutual and transitive ties) may highlight the notion that players involved in forming ties can change quarter to quarter, thus potentially capturing substitution patterns. Player substitution, or when an active player on the court is substituted with an inactive player from the bench, also reflects a change in game play strategy by changing the composition of the team on the court to work towards team outcomes.

Model 2 was used to assess *RQIII*, which included an edges and nodal attribute term for player position. *Figure 27* shows sample networks from a game played between the Toronto Raptors (TOR) and the Cleveland Cavaliers (CLE) to provide a high-level look at differential patterns in passing by player position. *Figure 27* suggests small forwards are not central to TOR's passing network for the observed game, and that power forwards, shooting guards and centers may be equally utilized. CLE appears to have a more distributed passing model with majority of its players sending and receiving passes, irrespective of player position.

Figure 27

TOR and CLE Game Network with Position

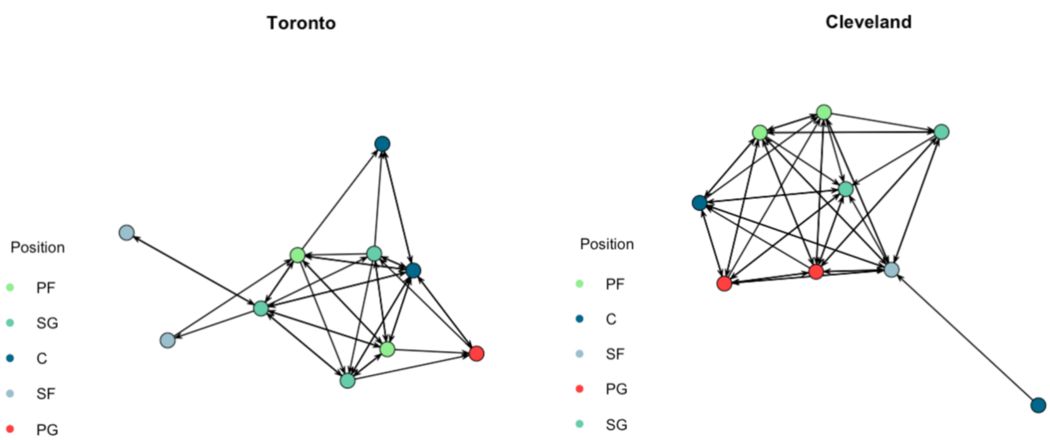


Table 23 shows model output for a game played between TOR and CLE as these were the top two teams of the Eastern Conference in the 2016-2017 NBA season. When assessing nodal attributes, the *nodeifactor* term, representing the impact of an attribute on in-bound passes, uses a baseline category (in this research, the baseline category is the *center* position). The term *Position.PF* provides a model coefficient that compares the likelihood that relation formation is explained by player position comparing passes for centers to passes for power forwards (PF), whereas the term *Position.PG* would compare centers to point guards (PG) and so on.

When assessing the impact of nodal attributes (i.e., player position), models to explain network patterns for TOR and CLE produce very different results. Negative model coefficients indicate the nodal attribute in question is less likely to explain network

Table 23

Results of STERGM Analyses for Game Between TOR and CLE

Model Term[1]	**Team**	
	CLE	**TOR**
Form~Edges	-2.53 (0.52)***	-1.32 (0.34)***
Form~Position.PF	1.04 (0.67)	-0.27 (0.52)
Form~Position.PG	1.63 (0.63)**	-2.12 (1.07)*
Form~Position.SF	2.01 (0.73)**	-2.21 (0.79)**
Form~Position.SG	1.16 (0.63)	-0.84 (0.49)
Persist~edges	-2.20 (1.05)*	-0.62 (0.47)
Persist~Position.PF	2.04 (1.13)	0.38 (0.62)
Persist~Position.PG	1.56 (1.13)	-15.75 (1085.19)
Persist~Position.SF	1.95 (1.17)	-15.28 (1217.59)
Persist~Position.SG	-0.44 (1.48)	-0.30 (0.67)
Iterations	5	14
AIC	306.52	286.80
BIC	343.15	325.67

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
[1]*Note.* All position terms are *nodeifactor* terms, which indicate the impact of an attribute on in-bound passes.

formation. All of TOR's position formation terms are negative, suggesting centers (i.e., the baseline category) have more incoming passes relative to the other positions in the formation model. In the persistence model, these patterns remain with the exception of the *Position.PF* term, suggesting that while centers were more likely to receive passes throughout the game relative to point guards, small forwards and shooting guards, power forwards were more likely to receive passes compared to centers throughout the game (although the coefficient is near zero; b = 0.38, probability = 0.59). Overall, these patterns suggest that throughout the observed game for TOR, centers are likely to be at the center of the passing networks. However, power forwards are slightly more likely than centers to receive incoming passes across the game relative to centers.

CLE's results suggest different patterns in passing behavior to explain their observed networks. All of CLE's formation terms are positive, indicating power forwards, point guards, small forwards and shooting guards are more likely to receive passes relative to centers. The highest coefficient for CLE's formation model is for *Position.SF*, indicating small forwards had the highest incidence of incoming passes relative to centers (b = 2.01, probability = 0.88), followed by point guards (b = 1.63, probability = .84). CLE's persistence model shows a higher likelihood of incoming passes for power forwards (b = 2.04, probability = .89), followed by small forwards (b = 1.95, probability = .88). These results suggest that incoming passes are more prevalent in CLE's passing network for the observed game for small forwards and point guards, and that over the course of a game, players occupying power forward and small forward positions are more likely to receive incoming passes from other players. These data indicate different passing strategies between TOR and CLE based on player position, with TOR using a more concentrated passing strategy focused on passing to centers, and CLE more likely to use a dispersed passing strategy, utilize small forwards at some point in the game, and utilize power forwards and small forwards across the game.

To assess patterns across teams for the full season, *Figure 28* and *Figure 29* show coefficient edge probabilities by team for the last 23 games played in the regular season for the formation and persistence models, respectively. The games were selected based on the 2016-20217 season trade deadline of February 18, 2017, to provide an examination of

Figure 28

Model 2 Edge Formation Probabilities by Team

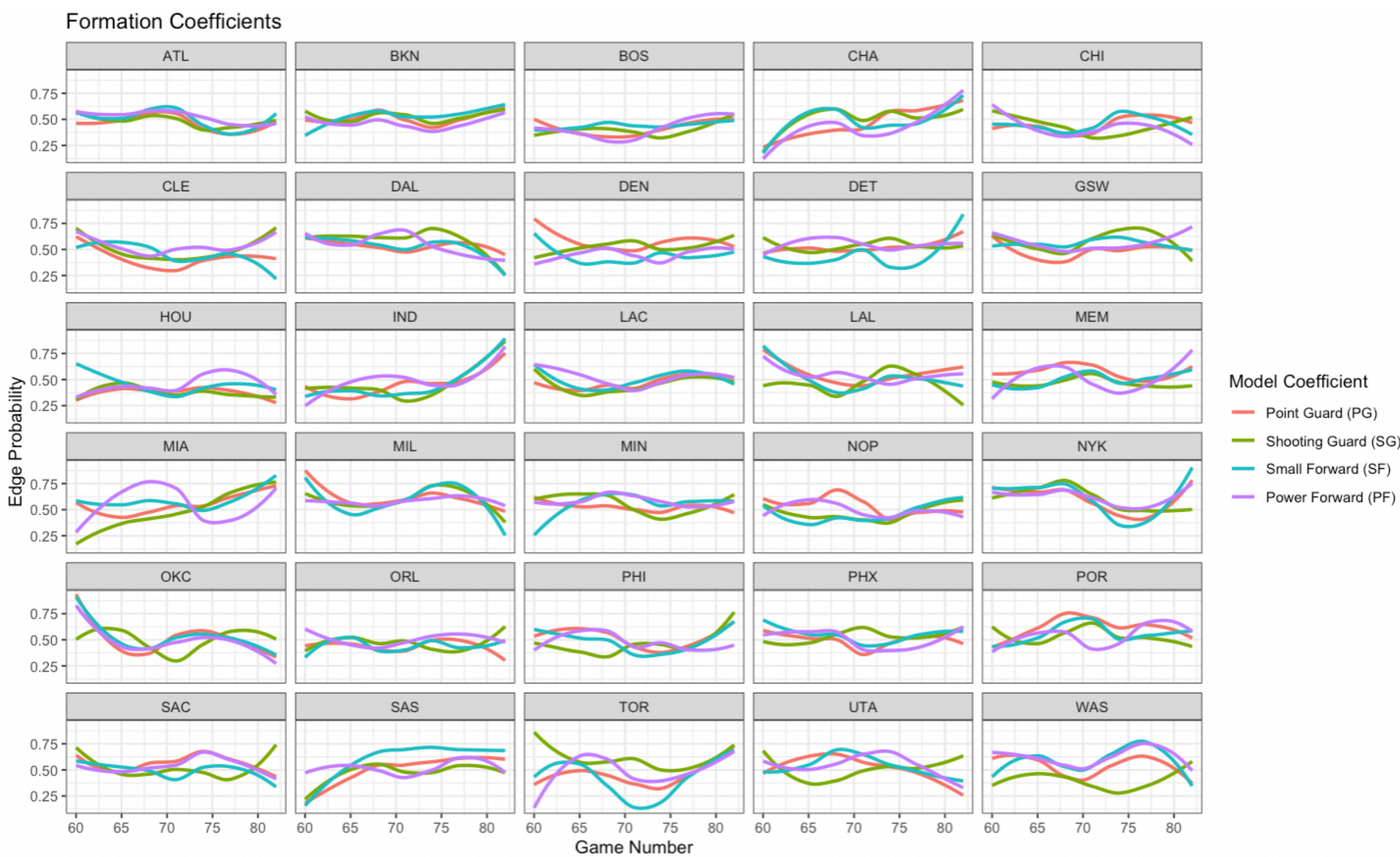


Figure 28. Model 2 (position model) edge formation probabilities across the last 22 games of the regular season. Model coefficients include *nodeifactor* (in-bound passes based on nodal attribute) for point guards, shooting guards, small forward, and power forwards, relative to centers.

Figure 29

Model 2 Edge Persistence Probabilities by Team

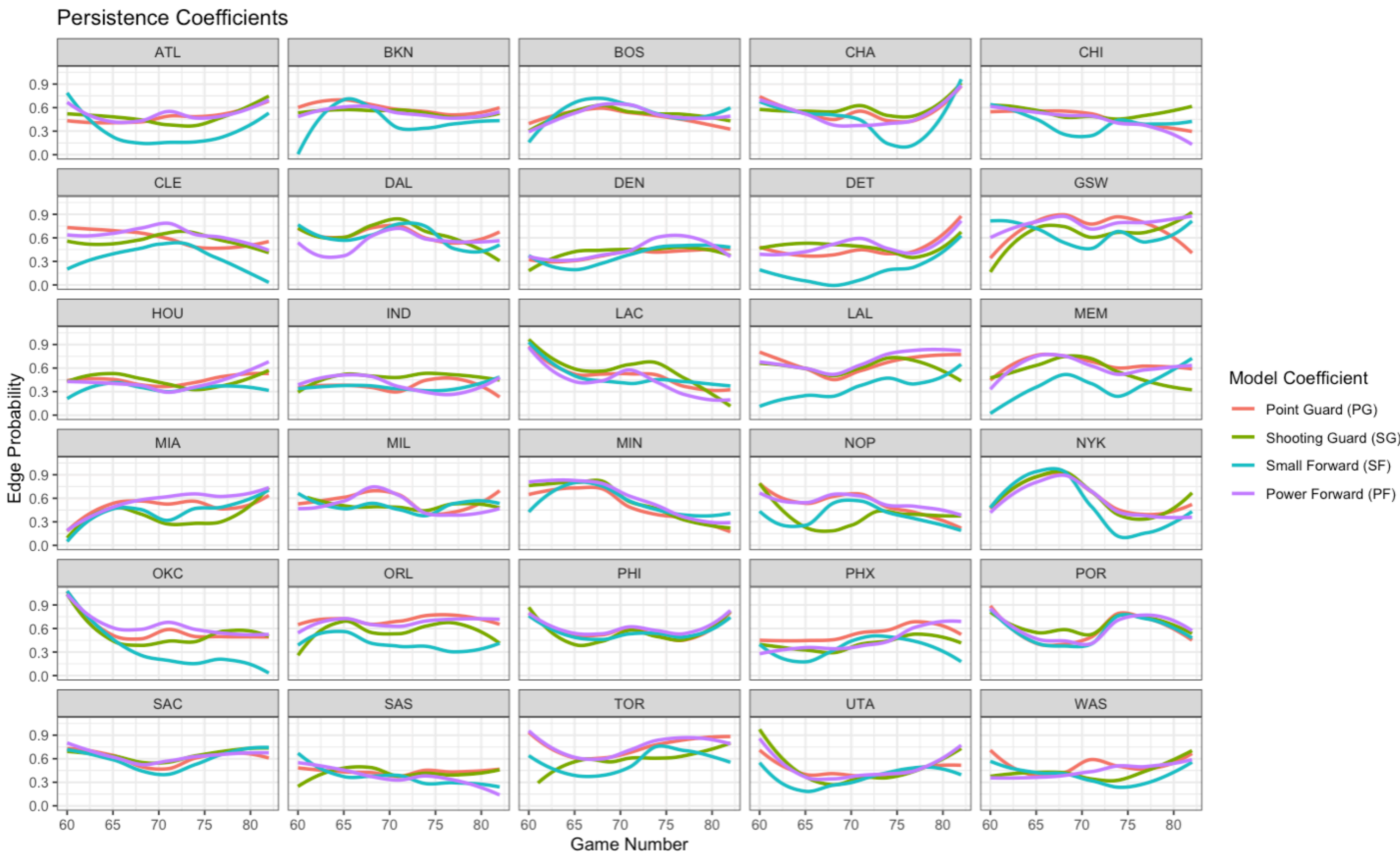


Figure 29. Model 2 (position model) edge persistence probabilities across the last 22 games of the regular season. Model coefficients include *nodeifactor* (in-bound passes based on nodal attribute) for point guards, shooting guards, small forward, and power forwards, relative to centers.

stable player positions for each team. In general, the impact of player position varies slightly across the observed games for both forming and maintaining passing relations. *Table 24* provides descriptive statistics for Model 2 terms for the teams across the observed games. Formation terms for all positions are at or near 0.50 probability, suggesting they are not more likely to explain network patterns than would be expected at random. The persistence term for power forwards (*PF*) ($M = 0.55$, $SD = 0.24$) and for point guards (*PG*) ($M = 0.55$, $SD = 0.24$) had the highest average probabilities across the season for explaining observed network patterns. In general, the persistence of position terms resulted in higher probabilities relative to the formation terms, with the exception of small forwards (*SF*). These data suggest that, relative to centers, the persistence of passing is more likely to be explained by in-bound passes to power forwards, point guards, and shooting guards. The persistence of passing is less likely to be explained by in-bound passes to small forwards ($M = 0.43$, $SD = 0.32$) relative to centers. These results could indicate that across all teams observed, throughout a game, passes are more consistently sent to power forwards, point guards and shooting guards relative to centers, potentially signaling a universal game play strategy based on player position. However, the probabilities are very small (i.e., barely over 50%), suggesting player position in-bound may not be used as a viable passing strategy for NBA teams.

Table 24

Model 2 Term Descriptive Statistics

Model Term	***M***	***SD***
Form ~ Edges	0.148	0.095
Form~ Power Forward (PF)	0.516	0.187
Form~ Point Guard (PG)	0.508	0.189

Form~ Small Forward (SF)	0.508	0.230
Form~ Shooting Guard (SG)	0.500	0.205
Persist~ Edges	0.273	0.156
Persist~ Power Forward (PF)	0.546	0.241
Persist~ Point Guard (PG)	0.548	0.238
Persist~ Small Forward (SF)	0.433	0.315
Persist~ Shooting Guard (SG)	0.524	0.265

Figure 30 visualizes the proportion of game/team combinations that meet five probability thresholds (i.e., 50%, 60%, 70%, 80% and 90%) across the season to further examine prominent nodal model terms. Overall, position terms in the persistence model resulted in higher probabilities relative to those in the formation model. In the formation model, small forwards (*SF*) had stronger probabilities across a higher proportion of games throughout the games observed (with 51% of games reaching at least 50% probability for this term). Only half of game/team combinations reach at least 50% probability for any position terms for relation formation, suggesting either (1) there is variance game to game for teams such that the probability of position impacting network behavior varies over time (over a season) or (2) that there is minimal effect of player position on relation formation. The persistence model tells a similar story, with approximately 50% of game-team combinations reaching at least 50% probability for the position terms for power forwards, point guards and shooting guards, and only 40% of game-team combinations reaching at least 50% probability for small forwards.

Figure 30

Model 2 Game/Team Combinations and Probability Thresholds

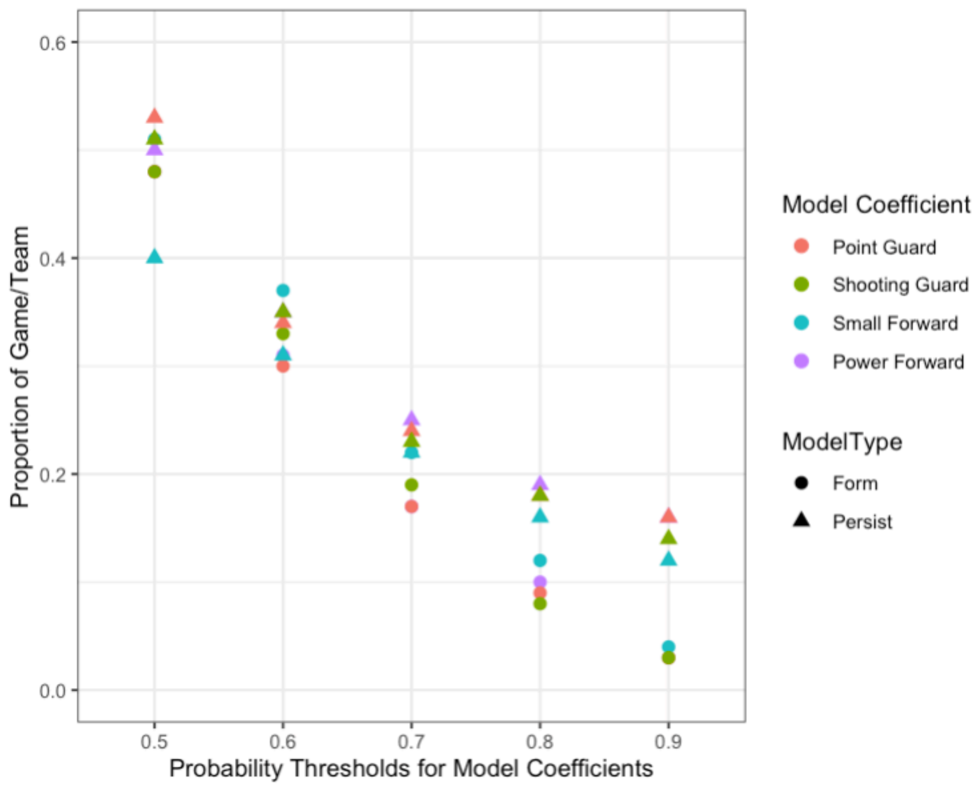


Figure 30. Figure 30 includes five probability thresholds to demonstrate the proportion of game/team network combinations that meet each threshold.

Given the variance observed in *Figure 28* and *Figure 29* and the large standard deviations observed when aggregating model output across all teams, a cluster analysis was conducted on Model 2 to identify if there were shared passing patterns based on position for the teams observed. Similar to the analysis used for Model 1, for each team, data were arranged by game number and model coefficient (position) for both the formation and persistence models to assess if similar season-wide strategies were deployed by teams, resulting in a 30 x 230 matrix (30 teams x 23 games x 10 model coefficients). Ward's method (1963) was used to generate clusters to minimize the distance to the center of a cluster within clusters and maximize the distance to the center between clusters. The distances obtained were centered to ensure data were internally consistent to enable adequate comparison. *Figure 31* shows a scree plot of the distances between clusters based on the number of groups used for analysis. Given the data and minimal differences across teams across the season, the plot elbows in more than one place, at two and four clusters. Given the exploratory nature of this research and to balance cluster size (i.e., the number of teams in each cluster), three groups were selected to analyze further.

Figure 31

Scree Plot for STERGM Model 2 Hierarchical Clustering

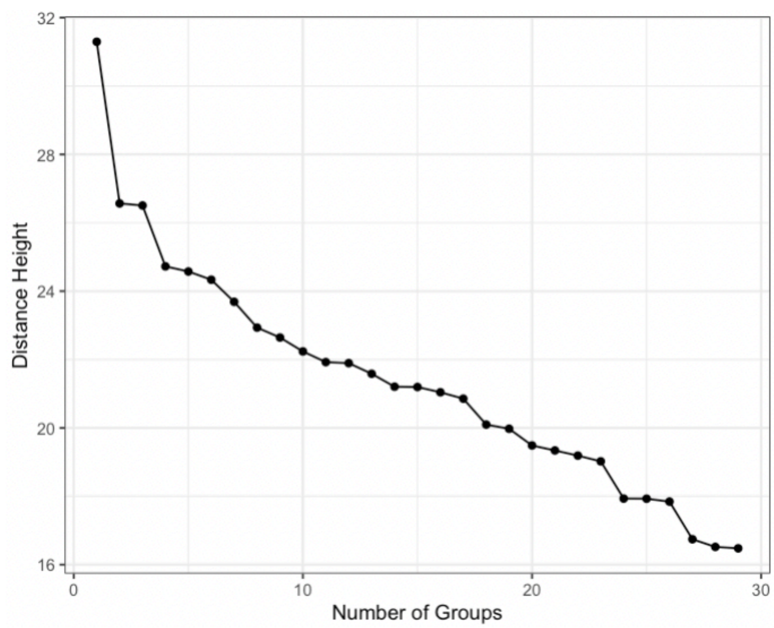


Figure 31. Scree plot demonstrating the decline in distance between clusters as the number of clusters selected increases.

The dendrogram in *Figure 32* summarizes the clustering output and visualizes the three clusters selected based on all 30 teams. Cluster 1 contains 10 teams (BKN, BOS, CHI, SAS, POR, UTA, LAC NOP, HOU, MIN), Cluster 2 contains 12 teams (ATL,

CHA, CLE, IND, MEM, ORL, PHI, DET, DEN, PHX, MIA, OKC), and Cluster 3 contains eight teams (MIL, WAS, DAL, NYK, SAC, GSW, LAL, TOR). Descriptive statistics for each cluster can be found in *Table 23*. Generally, data in *Table 23* suggest that across the games investigated (games 60-82), the average probability that being a point guard explains persistent in-bound passing is at least 50% in each cluster, with probabilities strongest in Cluster 3 (M = 0.63, SD = 0.28) relative to Cluster 1 (M = 0.50, SD = 0.22) and Cluster 2 (M = 0.53, SD = 0.24). Probabilities for in-bound passing based on position explaining observed networks were highest for teams in Cluster 3 for the remaining positions as well, for both the formation model (M_{PF} = 0.56, SD_{PF} = 0.17; M_{SF} = 0.54, SD_{SF} = 0.24; M_{SG} = 0.54, SD_{SG} = 0.21) and the persistence model (M_{PF} = 0.62, SD_{PF} = 0.29; M_{SF} = 0.52, SD_{SF} = 0.36; M_{SG} = 0.59, SD_{SG} = 0.31).

Figure 32

Dendrogram of Model 2 Cluster Analysis for All Teams

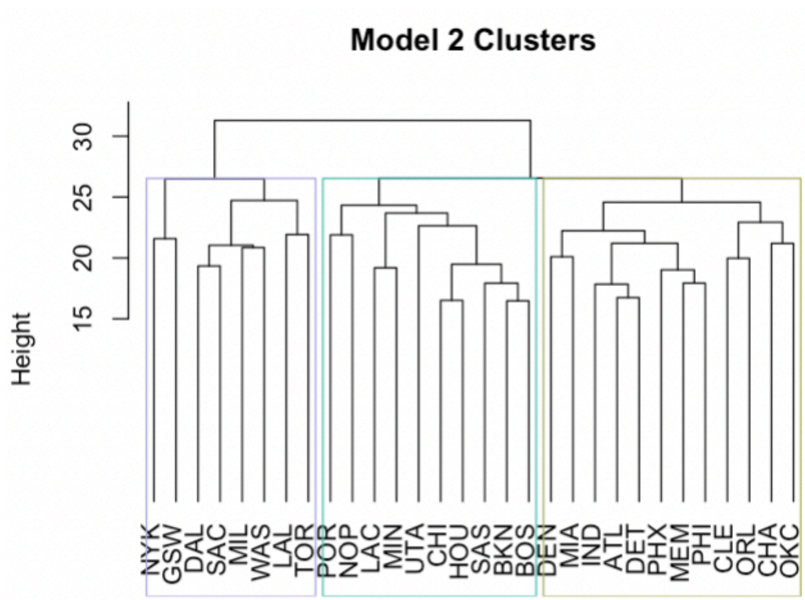


Figure 32. Dendrogram from Model 2 hierarchical cluster analysis showing the three selected clusters.

Table 25

TERGM Model 2 Cluster Descriptive Statistics

		Cluster 1		Cluster 2		Cluster 3	
Model	**Coefficient**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Form	Edges	0.16	0.20	0.15	0.09	0.13	0.08
Form	Power Forward	0.50	0.19	0.50	0.19	0.56	0.17
Form	Point Guard	0.49	0.19	0.50	0.18	0.54	0.19
Form	Small Forward	0.51	0.19	0.49	0.23	0.54	0.24
Form	Shooting Guard	0.47	0.21	0.49	0.19	0.54	0.21
Persist	Edges	0.30	0.15	0.30	0.16	0.21	0.17
Persist	Power Forward	0.49	0.23	0.55	0.23	0.62	0.29
Persist	Point Guard	0.50	0.22	0.53	0.24	0.63	0.28
Persist	Small Forward	0.44	0.29	0.37	0.31	0.52	0.36
Persist	Shooting Guard	0.50	0.24	0.50	0.25	0.59	0.31

Although differences are slight, the differences observed in Cluster 3 relative to Cluster 1 and Cluster 2 may suggest that teams differentially leverage player position as a passing strategy. Whereas *Table 25* provides an assessment of the three clusters at an aggregate level across the entire season, *Figure 33* visualizes how model coefficients change over time for each cluster from game to game to demonstrate if and how teams change their passing strategies based on player position throughout the last 23 games of the season. Across the games observed, Cluster 1 had relatively stable passing patterns based on player position, with its model term probabilities mainly between 0.45 and 0.55 and the persistence coefficients for point guards, power forwards and shooting guards being highest for game 60 and falling below 50% probability around game 75.

Figure 33

Average Coefficient Probabilities for STERGM Model 2 Clusters

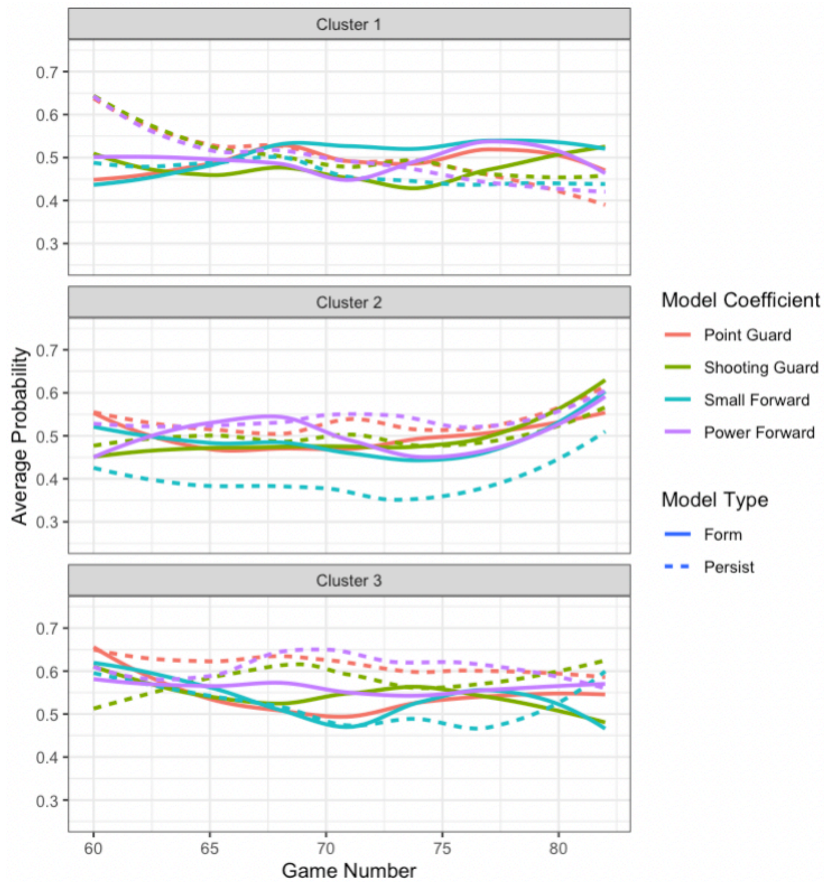


Figure 33. Average model coefficient probabilities across a season for teams by cluster. Solid lines represent formation terms, and dotted lines represent persistence terms.

Teams in Cluster 2 also had relatively stable model terms across the games observed with the formation coefficient for point guards, showing the greatest deviation from 50% probability, increasing over games 60 to 67, then dropping below 50% probability around game 72 and steadily increasing again after game 75. This deviation in probability could indicate a strategic shift in game play for these teams as playoff games approach in the latter portion of the season. Teams in Cluster 2 also saw the lowest probabilities for the persistence coefficient for shooting guards, with the values dropping as low as 35% probability around game 72 and increasing only up to 50% probability for two games in the observed time period.

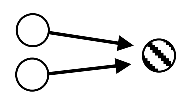
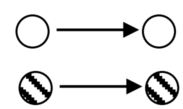
Teams in Cluster 3 had apparent increases in persistence terms relative to formation terms, apart from small forwards, suggesting strategies used tended to be maintained across quarters in a game rather than utilized strategically at certain points of a game. Probabilities for power forward, point guard and shooting guard were all well above 50%, with power forwards reaching the highest probability of all terms at 65% around game 70. Compared to Cluster 1 and Cluster 2, formation and persistence terms in Cluster 3, excluding small forward, stayed at or above 50% probability across the games observed, suggesting teams in Cluster 3 were more likely to leverage player position as part of their gameplay strategies.

Research Question III was posed to assess the impacts of player position on passing behavior for teams over time. Given the generally low probabilities across the season for the nodal covariate of player position, with only approximately half of game-team combinations for the networks observed resulting in model terms of at least 50% probability of explaining the observed network patterns, player position did not emerge as a consistent predictor of network behavior in NBA teams. However, the likelihood of player position predicting observed network patterns varies by team, with player position being more likely to explain the persistence of passing for a subset of teams (i.e., teams in Cluster 3 - MIL, WAS, DAL, NYK, SAC, GSW, LAL, TOR), suggesting player position might be used as a passing strategy for only a subset of teams.

To analyze Research Questions IV and V (RQ IV: How does scoring behavior impact passing?; RQ V: What is the comparative importance of network versus behavior change for teams within games?), SAOM was conducted using the *RSiena* package (Ripley et al., 2021). SAOM requires specifying model effects and creating an algorithm that will be used to estimate model parameters. The model effects included in SAOM (Model 3) were reciprocity, transitivity, covariate-related popularity (hereby referred to as *recipient scoring*), and covariate-related similarity (hereby referred to as *scoring similarity*). *Recipient scoring* models the degree to which the in-degrees of actors are impacted by a covariate and *scoring similarity* models the degree to which actors prefer ties to others with similar values on a covariate. *Table 26* provides a visual representation of *recipient scoring* and *scoring similarity*.

Table 26

Model 3 Covariate Terms

Effect	Model Term	Description	Basketball Applicability	Visual
Covariate-Related Popularity	*altX* (Referred to as *Recipient Scoring*)	Tendency for relations to form based on values of a covariate	Tendency for passes to be sent to a player based on how much a player has scored	
Covariate-Related Similarity	*simX* (Referred to as *Scoring Similarity*)	Tendency for relations to form based on similarity of a covariate	Tendency for passes to be sent to a player based on how similar a sending player's scoring is to a receiving player's scoring	

SAOM requires defining appropriate time periods for data aggregation. Given SAOM requires panel network data, and basketball quarters create natural breaks in game play, each game was broken into quarters and transformed into quarter-networks by team, resulting in 2,618 dynamic networks with anywhere between four and six networks for each game. As SAOM simulates behaviors that occur between timepoints to explain observed data (Leifeld & Cranmer, 2015), it requires post-simulation estimation to check for model convergence. Model convergence is achieved when a specified model can reproduce the observed behaviors beyond the second time period (Schaefer, 2019). If an initial model simulation did not achieve proper conversion (i.e., the *t* ratio was greater than 0.25), the model was re-estimated (Ripley et al., 2021).

t ratios are used to test for convergence in SAOM and indicate the extent to which parameter estimates are stable (i.e., that they converge across simulations) by comparing estimated parameter values to simulated parameter values (Kalish, 2020). *t* ratios close to 0 indicate simulated parameter values are the same as estimated parameter values. Although convergence thresholds are intended to serve as guidelines for convergence rather than severe limitations, excellent convergence is reached when the maximum *t* ratio for a model is less than 0.20 in absolute value and individual *t* ratios for parameter estimates are less than 0.10 in absolute value, reasonable convergence is reached when the maximum *t* ratio is less than 0.30 in absolute value, and a model is nearly converged when the maximum *t* ratio is less than 0.35 in absolute value when individual *t* ratios are less than 0.15 in absolute value. *t* ratios are obtained from deviations in parameter estimates. During simulation, parameter values for each model parameter are simulated and compared to observed values, which I will refer to as *simulated deviations*. Each parameter has a resulting *t* statistic, which takes the average simulated deviation of a parameter and divides that value by the standard deviation of all simulated deviations (Ripley et al., 2021).

Table 27 shows the distribution of maximum *t* ratios across all 2,618 models. While on average, maximum *t* ratios for the models show high average convergence (*M* = 2.43, *SD* = 17.70), the range is quite large, ranging from 0.02 to 758.89. Given the skewness of the data, the median may serve as a more meaningful statistic in assessing maximum *t* ratios. The median maximum *t* ratio across all models was 0.10, a value that indicates excellent convergence. *Table 28* shows the proportion of models that fell into the three convergence thresholds typically used in SAOM. 74% of models met the threshold for excellent convergence (< 0.20), 78% of models met the threshold for reasonable convergence (< 0.30), and 80% of models met the threshold for near convergence (< 0.35). To ensure results interpreted based on non-converged models are not misleading (Ripley et al., 2021), and given the exploratory nature of this research, the near convergence threshold was used as a filter for sufficient models for analysis (0.35), resulting in 529 models (Game/Team combinations) being omitted from further analysis (for a total of 2,089 models to further analyze).

Table 27

SAOM Overall Model Convergence Descriptive Statistics

	N	**Mean**	**SD**	**Median**	**Min**	**Max**	**Range**	**Skew**
Maximum *t* ratios	2,612*	2.43	17.70	0.10	0.02	758.89	758.87	31.64

**Six models failed to reach convergence, thus failing to produce t ratios.*

Table 28

SAOM Model Maximum Convergence Thresholds

Convergence Threshold	**N**	**Percentage of Models**
Excellent (< 0.20)	1,945	74%
Reasonable (< 0.30)	2,052	78%

Near Convergence (< 0.35)	2,089	80%

Table 29 shows descriptive statistics of individual parameter convergence across the remaining 2,089 models. The average value is close to excellent convergence (*M* = 0.01, *SD* = 0.06), with the median demonstrating perfect convergence (median = 0). There are also outliers in the data, as shown in *Table 30.* A vast majority of individual parameters demonstrated excellent (90% of model terms) or reasonable (97% of model terms) convergence. Model terms that did not reach reasonable convergence were omitted from further analysis.

Table 29

SAOM Individual Parameter Model Convergence Descriptive Statistics

	N	Mean	SD	Median	Min	Max	Range	Skew
Parameter *t* ratios	16,775	0.01	0.06	0	-0.35	0.33	0.68	-0.39

Table 30

SAOM Individual Parameter Convergence Thresholds

Convergence Threshold	N	Percentage of Models
Excellent (< 0.10)	15,074	90%
Reasonable (< 0.15)	16,218	97%

Table 31 shows output from Model 3 for a sample game played between Boston (BOS) and Toronto (TOR). For both BOS and TOR, all terms reached excellent convergence (< 0.10 in absolute value) and the maximum convergence ratios were 0.05 and 0.03 for BOS and TOR, respectively, indicating the simulated model values are close to target values. The rate function in SAOM indicates decision timing and assesses the

opportunity for actors to make a change between time points. Data in *Table 31* suggest that on average, BOS players were selected 10 times between timepoints (quarters) 1 and 2, 8 times between timepoints 2 and 3, and 8 times between timepoints 3 and 4, and TOR players were selected 11 times between time points 1 and 2, 7 times between timepoints 2 and 3, and 4 times between timepoints 3 and 4.

Table 31

Sample SOAM Output for TOR BOS

	BOS		TOR	
Coefficient (θ)	**Estimate (SE)**	***t* Ratio**	**Estimate**	***t* Ratio**
Rate constant (period 1)	10.40 (6.97)	0.03	11.20 (6.43)	0.01
Rate constant (period 2)	8.18 (3.70)	0.04	7.42 (4.26)	-0.02
Rate constant (period 3)	7.59 (6.53)	-0.01	3.90 (1.54)	0.01
Outdegree (density)	-2.16 (0.21)	-0.03	-1.57 (0.18)	-0.03
Mutual Ties	2.14 (0.39)	-0.05	1.24 (0.30)	-0.03
Transitive Ties	0.27 (0.07)	-0.03	0.26 (0.10)	-0.03
Recipient Scoring	0.09 (0.06)	-0.05	-0.01 (0.05)	-0.03
Scoring Similarity	0.63 (0.50)	0.04	-0.07 (0.66)	0.02

Positive model coefficients (θ) indicate that ties are more likely to occur based on an observed effect than without the observed effect, and negative model coefficients indicate ties are unlikely to occur based on an observed effect. Model effects can be translated into odds through the exp(θ) transformation, which informs the odds of adding a tie versus not adding a tie based on an observed coefficient. The outdegree parameters for both BOS (θ = -2.16) and TOR (θ = -1.57) are negative, indicating that the density of each team's passing networks decreases over time. However, this parameter primarily serves as a control for the density of the network, acting as a model intercept (Ripley et al., 2021). Reciprocity (θ_{BOS} = 2.14, TOR θ_{TOR} = 1.24) and transitivity (θ_{BOS}= 0.27, θ_{TOR}= estimate 0.26) for both teams are positive suggesting that over time, ties that create reciprocated or transitive relations are more likely to be added or maintained for both BOS and TOR. More specifically, the odds of adding/keeping reciprocated tie are 8.5 and 3.5 times the odds of adding/keeping a non-reciprocated tie for BOS and TOR, respectively, and the odds of adding/keeping a transitive tie are 1.3 times the odds of adding/keeping a non-transitive tie for both BOS and TOR.

The recipient scoring term is small for both BOS (θ = 0.09) and TOR (θ = -0.01), with the effect being negative for TOR. Although the effects are small, BOS's positive coefficient suggests that in this game, ties were more likely to be sent to players with higher scores and less likely for TOR (although both values are extremely close to zero, suggesting minimal effect). Specifically, for TOR, the odds of a player sending a tie to a player with a higher success rate of scoring points was as likely as a tie forming irrespective of player scores whereas for BOS, the odds of a tie forming based on player scores was 1.1 times more likely than ties forming irrespective of player scores. The scoring similarity term is positive for BOS (θ = 0.63) and negative for TOR (θ = -.07), suggesting that players were more likely to send passes to players who scored similar to them for BOS (e.g., if Player A, the sending player, had scored 10 points, Player B had scored 2 points, and Player C had scored 8 points, Player A was more likely to pass to Player C given the greater similarity in scoring 10 and 8 points relative to the similarity between scoring 10 and 2 points). This impact did not emerge for TOR. For TOR, the odds of a tie forming based on player scoring similarity was as likely as a tie forming irrespective of passing behavior whereas for BOS, the odds of a tie forming based on scoring similarity was 1.9 times more likely than ties forming irrespective of scoring similarity. Overall, these results suggest that for the observed game between BOS and TOR, players were more likely to pass to those who sent passes to them initially (mutual ties), and BOS players were more likely to pass to players who score similar to them (scoring similarity), suggesting creating mutual relations impacts player behavior in both teams and BOS players gravitate towards those with similar offensive skill levels.

Figure 34 shows the patterns of SAOM model coefficients for each team across the regular season (82 games). Generally, mutual ties consistently emerged as the highest coefficient across games across teams, with the values varying game to game. Scoring similarity varies greatly game to game with value magnitude changing over time depending on the game. Coefficients for transitive ties and recipient scoring are relatively consistent across the season for all teams, with transitive ties being slightly higher than recipient scoring, although both values are close to zero.

Table 32 shows descriptive statistics for model coefficients across game/team combinations for the entire season. Typical games will have three periods of simulation (one period between quarter 1 and 2, one period between quarter 2 and 3, and one period between quarter 3 and 4). Additional periods are simulated for games that go into overtime, with Period 4 representing simulation between quarter 4 and a first over time, and Period 5 representing simulation between a first and second overtime. On average, across the season for all games played by every team, players were selected 14 times between timepoints 1 and 2, 11 times between timepoints 2 and 3, 15 times between timepoints 3 and 4, 7 times between timepoints 4 and 5, and 3 times between timepoints 5 and 6 to make a change in their behavior. The drop off in selection for period 4 and

Figure 34

SAOM Model Coefficients by Team Across the Season

Figure 34. Model 3 (SAOM) model coefficient probabilities for each team across the regular 2016-2017 NBA season.

period 5 may be explained by shorter time allotted within overtime quarters for game play (teams only have five minutes of overtime game play compared to 12 minutes of regulation game play) and/or teams utilizing select, high-performing players given the game stakes in overtime.

Table 32

SAOM Model Coefficient Descriptive Statistics

	N	Mean	SD	Median	Min	Max
Rate constant (Period 1)	1,904	13.50	12.60	9.71	1.63	131.00
Rate constant (Period 2)	1,933	10.50	8.53	8.33	1.94	94.80
Rate constant (Period 3)	1,861	14.60	15.20	10.20	1.90	152.00
Rate constant (Period 4)	99	7.29	7.02	5.40	1.55	47.90
Rate constant (Period 5)	3	3.07	0.33	2.92	2.83	3.45
Outdegree (density)	1,899	-1.57	0.32	-1.56	-2.86	-0.46
Mutual Ties	1,881	1.41	0.40	1.38	0.21	3.42
Transitive Ties	1,821	0.23	0.07	0.22	-0.04	0.55
Recipient Scoring	1,940	0.01	0.06	0.01	-0.37	0.26
Scoring Similarity	1,944	0.08	0.51	0.07	-2.02	3.30

The recipient scoring and scoring similarity terms can be used to address RQIV (how does scoring impact passing behavior). The average coefficient across all game/team combinations for recipient scoring is 0.01 (*SD* = 0.06), indicating no effect, on average. The average coefficient for scoring similarity is 0.08 (*SD* = 0.51), equating to 1.1 odds of players forming ties based on scoring similarity. Given the low average, median and maximum values for the recipient scoring estimates and no teams having higher than 15% of their recipient scoring coefficients reach at least 1.1 odds, surprisingly, higher scoring does not result in players receiving more passes. *Figure 35* shows the proportion of scoring similarity estimates that meet one of five odds thresholds: 1 (no effect), 1.25, 1.50, 1.75 and 2.0 across teams. All teams have less than 25% of games analyzed reaching 2.0 odds for scoring similarity, with ORL having the highest proportion of estimates reaching 1.25 and 1.50 odds (67% and 46% of estimates, respectively). LAC, SAS, ATL, and ORL had the highest proportion of estimates reaching 2.0 odds (20%, 20%, 18% and 18%, respectively). With the exception of ORL, all teams had at least 25% of their games fail to reach an odds ratio of 1.0, suggesting for at least a quarter of games played, scoring similarity did not have an impact on passing behavior.

Figure 35

SAOM Scoring Similarity Estimates

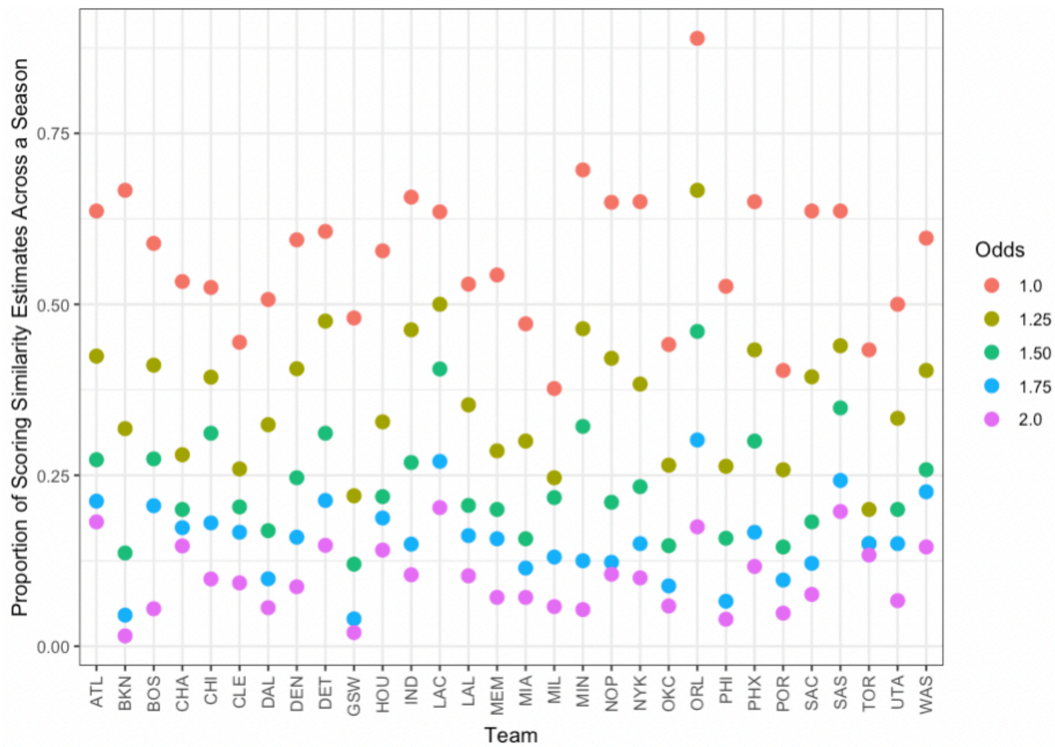


Figure 35. Proportion of odds ratios for scoring similarity estimates by team.

In games where the odds of scoring similarity impacting passing behavior are greater than 1.0, a player had a higher chance of receiving a pass from a player who has similar scoring behavior, potentially signaling a homophily effect of player behavior.

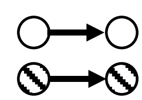
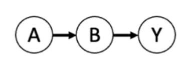
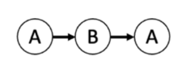
However, given the inconsistent patterns across a season for scoring similarity, and the lack of consistent estimates produced for recipient scoring, this research is not able to conclude that scoring behavior is a consistent factor impacting changes in network behavior.

To address RQV (what is the comparative importance of network versus behavior change for teams within games), the estimates for network terms (mutual and transitive ties) were compared to estimates for behavior change (recipient scoring and scoring similarity). Across game/team combinations for the games observed, mutual ties (M = 1.41, SD = 0.40, median = 1.38) and transitive ties (M = 0.23, SD = 0.07, median = 0.22) emerged as having higher odds relative to recipient scoring (M = 0.01, SD = 0.06, median = 0.01) and scoring similarity (M = 0.08, SD = 0.51, median = 0.07), with mutual ties emerging as the strongest estimate. The mutual ties coefficient indicates the odds of adding/keeping a mutual tie are 4.1 times the odds of adding/keeping a non-mutual tie generally across games. The odds of adding/keeping a transitive tie are 1.3 times the odds of adding/keeping a non-transitive tie generally across games. The data suggest that mutual ties, rather than network change generally, are more likely to occur consistently across games across a season. Given the inconsistent scoring similarity patterns across a season and the consistent near-zero recipient scoring values, the behavioral change examined for the teams observed is not more likely to occur relative to network change. It is possible that mutual passing occurs more naturally, and consistently, during basketball game play relative more intentional passing strategies, such as passing to similar scoring individuals or passing to higher scorers.

Finally, to analyze Research Questions VI-VIII (RQ VI: How do player attributes (i.e., player scoring) impact passing sequences? RQ VII: How does team context (i.e., home versus away game status) relate to passing sequences? RQ VIII: What passing sequences used throughout a game are associated with optimal team outcomes (i.e., team wins)?), REM analyses were conducted using the *relevent* package (Butts, 2015). For REM, the dependent variable is an interaction between two actors, and the goal is to assess which factors best predict the event's occurrence based on model effects. *Table 33* shows the five model effects included for REM, which were a covariate effect of player scores in each game, and four participation shifts: PSAB-BA, PSAB-BY, PSAB-XY and PSAB-AY.

Table 33

REM Model Effects

Effect	**Model Term**	**Description**	**Basketball Applicability**	**Visual**
Scores covariate	*covInt* (Referred to as *Scoring)*	Tendency for relations to form based on values of a covariate	Tendency for passes to be sent or received based on player scores	
Participation shift: turn receiving	*PSAB-BY*	General turn-receiving relational event	Tendency for passing to shift from Player A to Player B to Player Y	
Participation shift: turn receiving	*PSAB-BA*	Mutual ties	Tendency for passing to be reciprocataed between Player A and Player B	

Participation shift: turn continuing	*PSAB-AY*	Continued relational event from A	Tendency for passing to continue being sent by Player A to other players	A → B A → Y
Participation shift: turn usurping	*PSAB-XY*	Turn claiming	Tendency for passing to be claimed by a new player in the sequence	A → B X → Y

This research treated all possessions within a game for a team as a single, continued possession. While each individual possession could be treated as a network or possessions could be combined by quarter, this research opted to treat a game's worth of possessions as a single relational event sequence to assess to prominence of the proposed model terms throughout an entire game. Although turn usurping (AB-XY) and turn continuing (AB-AY) are not possible *within* a single possession for basketball teams (i.e., there must be continuity of passing between players), these terms are used in this research given this REM analysis combines all possessions into a single relational event sequence, allowing for the possibility of turn usurping and turn continuing *between* possessions.

Residual and model deviance values were used to assess REM fit. Residual deviance assesses the extent to which a response variable can be predicted by a model with p predictor variables and model deviance assesses the extent to which a REM deviates from an ideal model that fits the data perfectly. Of the 2,618 game/team combinations analyzed, model deviance for three models exceeded residual deviance, suggesting inadequate model fit (NOP game 70, SAC game 65, and MEM game 80). These three games were eliminated from further analysis, as were games played beyond the season standard of 82 games, resulting in 2,427 games.

Table 34 shows output from Model 4 for a sample game played between Chicago (CHI) and Detroit (DET). Model coefficients in REM are maximum likelihood estimates (MLE) that represent the odds or chance that a relational event (i.e., a pass) will occur based on the coefficient assessed and can be interpreted based on the exponential function of the coefficient – the higher a coefficient, the higher the odds that a relation will form based on the parameter in question. The *scoring* (*CovInt*) term assesses the impact that player scoring has on relations being formed in a game, including both outgoing and incoming actions (i.e., are relations formed based on how well players are scoring?). After accounting for all other effects, relations were slightly more likely to form when a player in a pair had high scores compared to a player in a pair having low scores for both CHI and DET, with this effect being stronger for DET (MLE = 0.14, *SE* = 0.01) than for CHI (MLE = 0.09, *SE* = 0.01) (although both effects signify weak effects given their magnitude). For DET, the odds that relations will be formed in a pair with higher scores is 1.15 times the odds of relations being formed in a pair with lower scores. Both turn receiving participation shift effects were positive for CHI and DET, suggesting reciprocity (PSAB-BA) and three-player continued passing (PSAB-BY) were likely effects impacting passing decisions. These effects were stronger for CHI PSAB-BA (MLE = 2.90, *SE*= 0.26) and PSAB-BY (MLE = 1.88, *SE* = 0.23) compared to DET PSAB-BA (MLE = 2.43, *SE* = 0.31) and PSAB-BY (MLE = 1.78, *SE* = 0.21). Turn usurping (PSAB-XY) was not a significant effect for either team (MLE_{CHI} = -1.06, SE_{CHI} = 0.29; MLE_{DET} = -2.14, SE_{DET} = 0.31) and passes continuously sent from one player to a range of other players (turn continuing; PSAB-AY) was only a prominent effect for DET (MLE = 0.25, *SE* = 0.29).

Table 34

Sample REM Output for CHI DET

	CHI		DET	
	Maximum Likelihood Estimate	**Standard Error**	**Maximum Likelihood Estimate**	**Standard Error**
Scoring (*CovInt*)	0.09	0.01	0.14	0.01
PSAB-BA	2.90	0.26	2.43	0.31
PSAB-BY	1.88	0.23	1.78	0.21
PSAB-XY	-1.06	0.29	-2.14	0.31
PSAB-AY	-0.16	0.36	0.25	0.29
Residual deviance	1156	-	1335	-
Model deviance	504	-	625	-
Win/Loss	Loss		Win	
Home/Away	Away		Home	

To assess how different passing sequences relate to team context (i.e., home versus away status) and team outcomes (i.e., win or lose), t-tests were conducted on this game. T-tests are used to test the significance of means between two samples (Gerald, 2018). Dependent t-tests are used when values in one sample affect the values in another sample. Specifically, when members in one group can be used to determine members in another group, the samples are said to be dependent. Independent t-tests are used when sample values are not matched to values in another sample and are used to compare two groups whose means do not depend on the other (Gerald, 2018). Although passing behavior for an offensive team (i.e., the passing data observed in these analyses) is inherently influenced by the behavior of the defensive team, because there is not a one-to-one dependence between players in one team to players in another team, as used in dependent t-tests, an independent t-test was conducted. For team context, the home team (DET; $M = 0.49$, $SD = 1.77$) did not have significantly higher MLEs for the five REM parameters assessed relative to the away team (CHI; *M* = 0.73, *SD* = 1.61, $t(8) = 0.23$, $p = 0.82$). For team outcomes, the winning team (DET; *M* = 0.49, *SD* = 1.77) did not have significantly higher MLEs for the five REM parameters assessed relative to the losing team (CHI; *M* = 0.73, *SD* = 1.61, $t(8) = 0.23$, $p = 0.82$).

Figure 36 shows the patterns of REM model coefficients for each team across the regular season games, and *Table* 35 shows descriptive statistics for REM coefficient estimates. The data show generally consistent trends in model coefficients for teams across games across the season, with mutual ties (PSAB-BA) emerging as the strongest effect relative to the other four effects modeled (*M* = 2.81, *SD* = 0.41), suggesting that on average, the odds of reciprocal passes occurring within a game are 16 times the odds of non-reciprocal passes occurring generally across the season. Following PSAB-BA, PSAB-BY emerged as the second strongest effect relative to the remaining three effects (*M* = 1.87, *SD* = 0.35) suggesting that on average, continuous passing from player A to player B to player Y (i.e., three-way passing) is 6.5 times the odds of non-continuous passing occurring generally across the season. Turn continuing (PSAB-AY) was the next strongest effect with an average coefficient of 0.20 (*SD* = 0.42) and turn usurping (PSAB-XY) was the weakest effect with an average coefficient of -1.47 (*SD* = 0.39).

It is not surprising that PSAB-BA and PSAB-BY are more prominent in the model relative to the other two participation shifts (PSAB-AY and PSAB-XY) given the nature of the data. Possessions were treated as continuous across a whole game to allow for examination of PSAB-AY and PSAB-XY. However, each possession is unique, thus instances in which PSAB-AY and PSAB-XY occurred could only exist at the start of a new possession, which does not truly model continuous passing behavior. Somewhat surprisingly, the scores covariate was not a significant parameter, hovering around zero for all game/team combinations (*M* = 0.05, *SD* = 0.04). In response to RQVI (how do player attributes (i.e., player scoring) impact passing sequences), the data suggest that, as found in SAOM, player scoring does not impact passing behavior. This is not surprising given the small effects detected in SAOM for scoring behavior, the stronger effects of network versus behavioral network patterns (SAOM), and the prominent effect of reciprocity and transitivity in the networks observed (both in SAOM and STERGM).

Table 35

REM Coefficient Descriptives Across Teams Across the Season

	Mean	**SD**	**Median**	**Min**	**Max**
Scoring (Cov.Int)	0.05	0.04	0.05	-0.27	0.20
PSAB-BA	2.81	0.41	2.82	0	4.05
PSAB-BY	1.87	0.35	1.90	-0.33	2.94
PSAB-AY	0.20	0.42	0.22	-2.14	1.50
PSAB-XY	-1.47	0.39	-1.45	-3.85	0

To address RQ VII (how does team context (i.e., home versus away game status) impact passing sequences), a one-way Multivariate Analysis of Variance (MANOVA) was performed to determine the effect of home versus away status on the three prominent REM model effects (PSAB-BA, PSAB-BY, PSAB-AY) as MANOVA is used to assess significant differences of one or more independent variables (in this case, home versus away status) based on a set of two or more dependent variables (in this case, three model terms) (Weinfurt, 1995). *Table 36* shows descriptive statistics for the three examined effects based on home versus away status across the season. The average effect for PSAB-BA for home teams was 2.82 (*SD* = 0.40) and 2.81 (*SD* = 0.41) for away teams;

Figure 36

REM Coefficients Across the Season

Figure 36. REM coefficient MLEs for each team across the regular 2016-2017 NBA season.

the average effect for PSAB-BY for home teams was 1.87 (*SD* = 0.35) and 1.86 (*SD* = 0.34) for away teams; the average effect for PSAB-AY for home teams was 0.19 (*SD* = 0.43) and 0.20 (*SD*= 0.42) for away teams. There was no statistically significant difference between home versus away status on the combined dependent variables (PSAB-BA, PSAB-BY, PSAB-AY), $F(3, 2611) = 0.51$, $p = 0.67$), suggesting team context did not impact the passing behavior observed.

Table 36

REM Home Versus Away Descriptive Statistics

	Home		**Away**	
	M	**SD**	**M**	**SD**
PSAB-BA	2.82	0.40	2.81	0.41
PSAB-BY	1.87	0.35	1.86	0.34
PSAB-AY	0.19	0.43	0.20	0.42

While home versus away status can impact player behavior given home teams have a "home court advantage" (Mizruchi, 1985; Entine & Small, 2008; Boudreaux, Sanders, & Walia, 2017; Perkins, 2017), this research did not find a link between home versus away status and passing behavior for the terms assessed. A possible explanation for the insignificant effects could be that home court advantage more closely relates to how successful actions are (i.e., points scored) versus passing behavior. Passing is the behavior that enables other actions to be taken (such as positioning the ball on the court to allow for two- versus three-point shots), so it is feasible that home court advantage best supports the success of actions versus the actions taken. In the 2016-2017 NBA season, home teams won 763 games compared to away teams winning only 546 games. A chi-square test of independence was conducted to assess the "home court advantage" on wins versus losses for the 2016-2017 NBA season, which finds that there is a significant association between home versus away status and wins and losses, $X^2(1, N = 2{,}618) = 71.29$, $p = .00$). Home teams were more likely to win games than away teams, supporting the notion that "home court advantage" positively impacts team *outcomes*.

To assess whether passing behavior related to team outcomes and address RQ VIII (what passing sequences used throughout a game are associated with optimal team outcomes (i.e., team wins)), a logistic regression was performed using the three prominent REM model effects (PSAB-BA, PSAB-BY, PSAB-AY) as predictors for winning or losing a game. *Table 37* shows descriptive statistics for the three examined effects based on win or loss status. The average PSAB-BA effect for winning teams was 2.81 (*SD* = 0.40) compared to 2.82 (*SD* = 0.41) for losing teams; the average PSAB-BY effect for winning teams was 1.87 (*SD* = 0.35) compared to 1.86 (*SD* = 0.34) for losing teams; the PSAB-AY effect for winning teams was 0.18 (*SD* = 0.44) compared to 0.21 (*SD* = 0.40) for losing teams.

Table 37

REM Win Versus Loss Descriptive Statistics

	Win		**Loss**	
	M	**SD**	**M**	**SD**
PSAB-BA	2.81	0.40	2.82	0.41
PSAB-BY	1.87	0.35	1.86	0.34
PSAB-AY	0.18	0.44	0.21	0.40

The logistic regression model, shown in *Table 38,* shows only a single significant effect, which is a small, negative effect for the PSAB-AY passing sequence such that, all else being equal, the odds ratio of winning a game using PSAB-AY as a passing strategy is 45% lower than not using this strategy (OR = 0.82, 95% CI [0.67, 1.00]). Given the non-significant differences in two of the three model terms and the small relation between PSAB-AY and winning/losing games, the observed passing strategies did not appear to have an effect on team outcomes. This is not entirely surprising given the variance in REM coefficients for teams across the season (shown in *Figure 36*), suggesting teams may deploy different passing strategies across games. Moreover, the level of granularity used when analyzing relational event sequences may be too nuanced to link to higher-level phenomena, such as games won or lost.

Table 38

REM Logistic Regression Output

	β	**SE**	**Odds Ratio (Exp(β))**	**95% CI**
Intercept	0.06	0.30	1.06	[0.59, 1.09]
PSAB-BA	-0.04	0.12	0.96	[0.90, 1.04]
PSAB-BY	0.05	0.14	1.04	[0.79, 1.39]
PSAB-AY	-0.20*	0.10	0.82	[0.67, 1.00]

**$p < .05$, *$p = .05$

Discussion

The purpose of this dissertation was to provide a descriptive foundation for future research using theories of time to study team phenomena by examining behaviors responsible for interaction patterns amongst team members and to demonstrate the utility of dynamic network models. This research provided a theoretical and mathematical description of three dynamic network methods along with providing an analytical example of each method used to explore team processes.

STERGM

STERGM models the temporal evolution of a network by considering an observed network based on all previously observed networks, which enables researchers to capture dynamic properties that drive network change over time (Guo et al., 2007). STERGM is unique in its assessment of how relations *form* and *dissolve* as it assumes that edge formation and edge dissolution are independent of one another, allowing for researchers to examine differential behaviors that drive various outcomes. Using STERM analyses, this dissertation found that both mutual and transitive passing relations for NBA teams in the 2016-2017 season explain the observed networks. Mutual passing relation formation was the strongest factor in predicting network patterns across teams, followed by mutual passing persistence, transitive passing formation, and transitive passing persistence. These results suggest that across teams across games, there is a strong likelihood that mutual passing will occur at some point during the game.

These results are not surprising given the high interdependence amongst basketball players during game play, and the relatively straight forward strategies of reciprocating passes and creating transitive relations. Moreover, the persistence of mutual passing might suggest that this strategy is used over time throughout gameplay rather than being strategically deployed during game play. It is also likely that transitive relations will form amongst three players on a team during game play and that these relations remain throughout a game. Formation terms generally emerged as having stronger probabilities relative to persistence terms. Formation terms suggest that the observed relationship occurs *at some point* during game play. Persistence terms suggest that observed relationships *are maintained across* game play. The stronger prevalence of formation terms may capture substitution patterns during game play. Teams can use player substitution as a strategy to change the composition of the team on the court in response to opponent strategy or as an intervention strategy when the current team composition is not performing well. This can make it difficult to maintain mutual and transitive passing relations if players are being substituted in and out as relations are forming. These patterns of mutual and transitive passing did not differ across teams based on a cluster analysis, suggesting mutual and transitive relations may be inherent in the passing structures of highly interdependent teams.

A supplemental logistic regression was conducted to assess if different passing strategies were deployed by winning versus losing teams (see *Appendix* for additional details). Across all game/team combinations, no significant effects were found for predicting wins and losses for persistence model terms (i.e., edges, mutual ties, and transitive ties), and logistic regression model coefficients were near zero for all three terms. However, significant effects were found for formation terms such that increased use of the general passing (edges) (OR = 0.37, 95% CI [1.00, 2.76]), mutual passing (OR = 0.20, 95% CI [1.11, 1.88]) and transitive passing (OR = 0.49, 95% CI [1.00, 1.50]) increase the likelihood of winning games. These results suggest that winning teams may more consistently use mutual and transitive passing as a viable game play strategy.

This research did not identify strong effects for player position on passing behavior based on STERGM analyses. Across the season, the persistence of passes being sent to power forwards and point guards emerged as the strongest coefficients, especially for MIL, WAS, DAL, NYK, SAC, GSW, LAL and TOR. For these eight teams, player position partially explains the observed passing behaviors. The higher probabilities of passes sent to point guards is not surprising given their high passing responsibility (i.e., point guards typically start plays when a team gains or re-gains possession). It is worth noting that a high degree of in-bound passes to point guards throughout game play could also reinforce the importance of point guards in re-setting players on the court if deployed strategies are not working effectively. For example, if a team tried a strategy in which they sent the ball directly to centers, but centers were being heavily defended by the defensive team, it makes sense that a center would send the ball back to the point guard to re-set and try another strategy, which could represent real-time shifts in game play strategy.

Power forwards also received slightly more passes relative to centers. However, the incidence of passing is higher for point guards and power forwards for only a subset of teams which may be indicative of game play strategy. Specifically, point guards for these teams appear more likely to receive passes during game play which could signal greater ball movement on the court (i.e., as opposed to a point guard initiating passes to positions with greater scoring responsibility). A higher likelihood of passes to power forwards for these teams could also indicate strategic selection of which positions are selected to take shots, potentially based on the skill of power forwards or a dynamically recognized offensive opportunity for power forwards to have access to the basket based on how a team is playing defense.

The formation and persistence coefficients for each model term for each team across a season demonstrates the unique capability of STERGM in modeling temporal evolution by differentially specifying formation and persistence passing patterns. While the coefficients were not drastically different relative to one another in aggregate, they show how the formation of different relations can be entirely separate from how relations are maintained. For example, MIN passing was best explained by the formation of mutual passes, followed by the persistence of transitive passes, the persistence of mutual passes, and the formation of transitive passes. Given the deviance between mutual formation and persistence and the deviance between transitive persistence and formation, the factors that resulted in formation likely differ from the factors that resulted in persistence. Perhaps during game play, mutual passes occurred strategically given they existed generally (formation) but were less likely to persist within each quarter. Alternatively, this could demonstrate the notion of substituting team members at the start of the quarter, which could inhibit continued passing relations. The larger effect for forming mutual passes relative to the other model terms, namely transitive passing, could signal the more complex nature of forming transitive relationships. The persistence of transitive passes emerged as more prominent relative to the formation of transitive passes which could suggest that when transitive passes occurred for MIN during game play, it was more likely to occur throughout the entire duration of a game (persistence) rather than just at some point during gameplay (formation).

Another example is the passing patterns that emerged for HOU. For HOU players, the formation of mutual passing was the strongest coefficient for the first half of the season, but towards the second half of the season, the persistence of mutual passing became more prominent. Whereas the first half of the season saw a stronger likelihood of mutual passes occurring generally, as observed for all teams across the season, the second half of HOU's season saw a stronger likelihood of mutual passing patterns being maintained quarter to quarter. This might suggest a shift in gameplay strategy midseason, potentially a result of increased trust between players, or could suggest changes in substitution patterns. This is useful for further understanding the composition of players on the court and could allow for examination of which players should play together and for how long. These two examples of separating out formation and persistence terms highlights areas in which different interaction mechanisms may differentially impact team processes.

SAOM

SAOM represents network evolution using an actor-based simulation (Ripley et al., 2021). While STERGM models the likelihood of events occurring based on observed networks, SAOM models how networks evolve between observed timepoints. The actor-orientation used in SAOM implies all changes in relations are determined by actors within the network. This dissertation used SAOM to assess the impact of both network and behavioral actions for the observed networks. Behavioral effects were defined based on how many points players scored. First, scoring similarity between players was assessed (i.e., did more passes occur between players who score like one another). This research did not find strong effects for scoring similarity. This is not entirely surprising given each player has a unique role on the court and scoring behavior can vary greatly between players. Even if two players score similarly, *how* they score points can be quite different. Moreover, scoring behavior is quite variable during game play, and it is impacted by contextual variables, such as who is defending a player and the opposing team's defensive strategy. However, behavioral similarity in SAOM can still be applied to more theoretically driven research questions focused on homophily, such as how gender or occupation impact the formation of groups (Ruef, Aldrich & Carter, 2003).

This research also examined how the degree of scoring for each player generally impacted passing behavior (i.e., were more passes sent to players who scores more points). Although this may seem like a popular strategy (i.e., pass to those who are preforming better), this research did not find strong effects for passing to players with higher scores. This is somewhat surprising as one can presume that team members that are performing well (i.e., scoring more) would be given greater opportunities to continue performing well (i.e., be given more passes). A potential explanation is that teams adopt passing strategies that involve passing to less-expected players. For example, if a player is consistently scoring, the defensive team may be more inclined to defend that player, so the offensive team may respond by moving the ball to a player that has a weaker defense to increase the chances of scoring success. Another potential explanation relates to the nature of SAOM analyses. This approach may overlook the strategies that lead to successful and non-successful scoring behavior. For example, if a team deployed a strategy to pass the ball to all five players on the court with the fifth player designated to take a shot (as this player had the highest success with scoring previously), SAOM would treat each pass between the first and fifth player equally, which could result in an inaccurate comparison of in-bound passing based on player scoring. SAOM would count the first three passes as passes to lower scoring players, and only count the final pass as a pass to a higher scoring player, which neglects the strategic path taken to get the ball to the highest scoring player.

SAOM also allows researchers to compare the importance of network versus behavioral change within networks. This research included assessing mutual and transitive ties as simple network terms to compare to the two behavioral terms (similar scoring and recipient scoring). Given the insignificant effects of the behavioral terms, the network terms better explained the observed networks. Specifically, mutual ties emerged as the strongest term in the model across games across the season relative to the other terms assessed, followed by transitive ties. This pattern follows those found in STERGM analyses, providing additional support for the ubiquity of mutual and transitive passes amongst NBA basketball teams. It is likely that the nature of this research is a key reason for this finding as prior research has found significant effects for behavioral terms after controlling for network effects (see Kalish, 2020). This research did not collect detailed behavioral data that may have provided more insight into player passing behavior such as personality, physical aptitude, or hours of sleep players were playing on. Although the behavioral effects evaluated in this dissertation were not strong, this research demonstrated the unique capability of SAOM in simultaneously modeling network and behavioral actions taken by team members.

REM

Of the three analytical methods examined in this paper, REM most closely models behavioral emergence. REM utilizes discrete and continuous data for analysis, assessing relational events rather than relational states. This allows for an examination of unique actions that occur from one individual to the next, moving analyses beyond the individual level to a single interaction. This research used REM to analyze four types of REM sequences and address how player attributes (i.e., scoring) impact passing sequences. Of the four passing sequences analyzed, PSAB-BA (reciprocity) and PSAB-BY were the strongest (PSAB-AY produced small model coefficients and PSAB-XY produced negative model coefficients). These results are not surprising given reciprocity was identified as the strongest passing pattern to explain network behavior in both STERGM and SAOM. It is also not surprising that PSAB-BY emerged as a strong coefficient. For basketball teams, this is a passing sequence in which three players are involved and the ball is moved across the players (from Player A to Player B to Player Y). This sequence indicates turn continuation, which is necessary for transitivity to occur (which was found to be a significant model coefficient in both STERGM and SAOM). PSAB-AY and PSAB-XY were included in analyses for demonstration purposes, and their insignificance to these results is to be expected. PSAB-AY and PSAB-XY sequences only make logical sense for data in which the recipient of an action does not need to be the sender of the next action. The continuity of passing sequences used for REM analyses in this dissertation allowed these sequences to be modeled, but in basketball game play, it is not possible for these sequences to exist. This research also did not find a significant effect of player scoring on passing behavior. Player scoring in REM was modeled as a covariate effect for both outgoing and incoming actions (Butts, 2015). These results suggest that relations are not more likely to form between players based on how well players are scoring (i.e., if players are scoring more).

This dissertation also used REM to examine how team context (i.e., home versus away status) relates to passing sequences. Teams can experience a “home court advantage” in which home teams have the benefit of operating in a familiar environment with minimized travel distances prior to gameplay (relative to away teams) and with fans providing social support and motivation throughout a game (Mizruchi, 1985; Entine & Small, 2008; Boudreaux et al., 2017). However, this research did not find an effect of home versus away status on passing sequences. This is not entirely surprising considering no additional contextual variables were controlled for, and the variables that are theorized to link to a "home court advantage" (i.e., social support, motivation, familiar environment, travel distance) were not directly assessed in this research. This research did, however, provide an illustration of how contextual variables can be integrated into REM research by creatively linking different analytical approaches (i.e., REM and MANOVA).

Finally, this research also assessed team outcomes – specifically, what passing sequences are associated with optimal team outcomes (i.e., team wins). This research found a small, negative effect for PSAB-AY on game wins/losses, suggesting that the odds ratio of winning a game using this passing strategy is lower than losing at random (50/50 odds). However, given PSAB-AY is not a true possible continuous passing sequence for basketball teams, this research does not conclude this as a significant effect. A possible explanation for why the other model terms found to be significant in this research (such as PSAB-BA and PSAB-BY) did not relate winning or losing games could be due a micro versus macro perspective. Multi-level theory highlights the importance of time when analyzing multi-level data. Specifically, lower-level phenomena (in this case, relational event sequences) have more rapid dynamics relative to higher-level phenomena (e.g., team wins or losses) (Kozlowski & Klein, 2000). The nuanced passing sequences examined at the interaction level may more readily explain team outcomes at a similarly nuanced level (such as at the possession level) compared to higher-level phenomena (wins and losses). Alternatively, the lack of relation of these passing sequences to team outcomes might suggest that these passing sequences are more generalized to basketball game play for all teams rather than serving as a differentiated competitive advantage for winning teams.

Interestingly, mutual ties (PSAB-BA) analyzed in REM did not relate to team outcomes (i.e., wins versus losses), but the formation of mutual ties analyzed in STERGM did relate to team outcomes (i.e., winning teams had stronger coefficients for forming mutual ties). Similar for passes involving three players, three-player sequences (PSAB-BY) modeled in REM were not significantly related to team wins whereas transitive relations (the formation of transitive ties) modeled in STERGM did relate to team wins. One possible explanation is that STERM highlights how dynamics that impact the formation of relations versus the persistence of relations can differ. Specifically, STERGM would suggest that forming mutual and transitive ties during game play might be deployed strategically in certain quarters for winning teams (versus *maintaining* mutual and transitive ties throughout a game), whereas REM would suggest that using mutual passing (PSAB-BA) or three-player passing (PSAB-BY) continuously throughout a game is not a differentiating strategy for winning teams. This difference in strategy success for seemingly similar model terms highlights the utility of using multiple analytical approaches when studying team processes.

Theoretical Implications

Organizations and organizational researchers can benefit from the three dynamic network models studied in this dissertation. Teams researchers frequently use the I-P-O and IMOI frameworks to facilitate the study of teamwork (Hackman, 1987; Ilgen et al., 2005). However, empirical research lags with respect to rigorously measuring and assessing team processes over time. Leenders and colleagues (2016) highlight four key limitations to the empirical investigation of teamwork that this research addressed.

A first limitation to studying team processes is measuring team process as an aggregated summary index (Leenders et al., 2016). This dissertation identified three dynamic network methods that minimize data aggregation and instead use more granular behavioral data. STERGM and SAOM are time-based analyses that require some aggregation of data (i.e., creating edgelists that capture connections between two individuals within a specified time frame), avoiding the need for a single summary statistic to represent a team. REM requires no aggregation of data, protecting the granularity of the raw observed data. Limiting the aggregation of team data helps to protect researchers against losing any critical details from aggregation. The nuanced data and limited aggregation used in this research allowed for the detection of various relational strategies (e.g., mutual ties, transitive ties) at a dyadic level that otherwise could be lost by aggregating self-reported data on relations that formed within the teams observed.

A second limitation to studying teamwork is assuming homogeneity of interactions between all team members (Leenders et al., 2016). When interactions are aggregated to represent a team, information on individual and dyadic behavior is lost. This dissertation showed the importance of mutual and transitive passing relations, which focus on behavior between two and three individuals, respectively. Moreover, for a select few game/team combinations, the persistence of in-bound passes to point guards slightly explained observed network behaviors, highlighting the importance of recognizing individual differences in team behavior. By taking individual-level constructs and assessing their impact at a team level, rather than using a single summary index to represent a group of diverse individuals, these dynamic network models allow for an investigation of how individual behaviors differentially evolve over time amongst different individuals. While this research did not find strong, consistent effects of player position or scoring behavior on passing behavior, the three methodologies assessed in this research provide researchers with a way to assess how individual attributes impact interdependent behaviors within teams.

A third limitation of studying teamwork this research addressed is the reliance on underdeveloped theories of teamwork with respect to time scales (Leenders et al., 2016; Mitchell & James, 2001). Typically, empirical studies measure teamwork for only a few, poorly specified performance episodes, which may result in missing critical information on how team members perform their work over time. To truly capture team process, researchers must consider the most appropriate methods for studying intricate behaviors at the lowest level possible to assess the emergence of behaviors throughout performance episodes. By capturing data at the most granular level, researchers have the flexibility to identify the most appropriate timepoints for aggregation when necessary (i.e., when using STERGM and SAOM) or to leverage interaction-level data to understand behavioral evolution over time (i.e., when using REM). STERGM and SOAM provide an examination of how relationship formation and maintenance between any two individuals evolves over time, which can provide information on team processes altogether. REM is the most sophisticated of the three dynamic network methods studied with respect to time given its use of continuous data. Since no data aggregation is required, REM enables researchers to explore how team processes unfold, action by action, which provides a detailed look at constantly evolving team strategies over time.

A fourth limitation of studying teamwork is assuming repeated measurements capture team process more granularly (Leenders et al., 2016). Repeated measurements of aggregated team processes and interactions may provide some insight into aggregated contemporaneous and lagged effects, but it does not provide granular information on how team members accomplish their work. While STERGM and SAOM treat data as longitudinal panel data during analysis, fine-grained individual and relational data can be used to create a set of panel data. There are infinite options when creating panel data based on such nuanced individual-level data – an approach which is not possible to do when only a single observation is gathered at pre-specified time points. Given the continuous data leveraged in REM, there is no need to break data into panels for assessment, enabling researchers to assess specific relational sequences that predict future behavior.

Practical Implications

STERGM, SAOM and REM are useful methods for exploring interdependent behavior within organizations. While the data collection effort in this paper was lengthy and rigorous, relational data within organizations is often collected but is not always leveraged. For example, most organizations rely on email and calendar management platforms, such as Microsoft Outlook and Gmail. These platforms can track all emails and instant messages sent and received within an organizational network, along with information on who is meeting, when they are meeting and for how long. Additional information on email and calendar data includes subject lines (e.g., what is the email or meeting regarding) and email and meeting attachments (e.g., any related documentation). Email, messaging, and calendar data represent nuanced interactions, such as who is involved in certain conversations, how frequently teams communicate and meet, and how they spend their time when they do meet. While there are data privacy and accessibility concerns regarding email, messaging, and calendar data that organizations must consider before using the data, the data exist and do not require arduous data collection efforts. Organizations can also leverage sociometric badges, or wearable electronic devices that capture person-to-person interactions, including physical proximity and conversational time (Kim, McFee, Olguin, Waber & Pentland, 2012), to collect fine-grained team interaction data.

A key benefit to leveraging relational data is the ability to enhance organizational outcomes. Teams generally exist within organizations to produce outputs. When teams fall short of expectations, it is useful for organizations to intervene to enhance performance. By using granular data to assess team processes, organizational practitioners can identify how interaction patterns relate to team outcomes and assess which interaction patterns result in optimal outcomes. A primary outcome of interest to organizations is team performance, which can be defined differently based on organizational goals. Given STERGM, SAOM and REM require collecting time-based data, practitioners can identify time points for analysis based on their intervention goals. They can also capture performance data that matches the time points specified to assess the relationship between the observed relational data and performance at given time points. By integrating relational data with performance data, organizations can identify optimal relational patterns and behaviors for success and intervene when performance is dropping below expectations.

Assessing relational data can also inform organizations on their diversity and inclusion (D&I) efforts. Diversity is defined as surface or deep-level characteristics of individuals that differ (Bell et al., 2011). These characteristics can include visible attributes (e.g., age, race, gender) or hidden attributes (e.g., educational background, personality). Inclusion refers to the acceptance and belongingness of diverse individuals (Hays-Thomas, 2017). Research suggests diversity increases organizational outcomes, such as attracting talent and customers and increased financial returns (Herring, 2009; Singal, 2014; Bell et al., 2011; Hunt, Layton & Prince, 2015; Hoobler, Masterson, Nkomo, & Michel, 2016). The three dynamic network methods studied in this paper allow organizational practitioners to assess how relations formed within organizations are impacted by diversity-related variables. This is especially critical for inclusion efforts, as organizations can examine if and where silos in communication are occurring amongst teams and groups. For example, using SAOM would allow practitioners to assess if new team members are being included within their teams and can unveil if certain relational patterns (such as sending or reciprocating communications) are more likely to occur amongst those who share demographic variables. This can enable organizations to investigate where they need to dedicate resources to support D&I efforts and provide data to track their progress on D&I initiatives.

Nudge theory can be used to further the organizational assessment of performance and D&I within organizations. Organizations are increasingly considering/adopting the use of “nudges” to reinforce and direct individual behavior (Kosters & Van der Heijden, 2015). For example, organizations can nudge an employee with a reminder to complete an online training. Nudges are intended to produce specified outcomes from individuals. To enhance team performance or inclusion, knowing how interactions change over time can inform organizations of when and where to nudge teams. For example, organizations can nudge teams to enhance the degree of information being shared and how to share information (e.g., share frequently, reciprocate information) if previous examinations of team communication suggest team information sharing has decreased over time for certain teams and has resulted in poor performance. For D&I efforts, organizations can nudge team leaders to check-in with diverse team members to enhance inclusion when communication patterns are not as strong for minority individuals. STERGM, SAOM and REM can enable organizations to enhance the efficiency and effectiveness of organizational interventions by assessing actions and processes that directly relate to certain outcomes and targeting specific actions at specific times (Braun et al., 2022).

Limitations

This study had several limitations. The biggest limitation involved the treatment of the data collected. Specifically, the raw data included both passing sequences and game play actions (e.g., taking field goal shots, securing rebounds). To obtain the passing sequence edge lists, all game play actions, with the exception of passes between players, were removed from further use. As a result, many player actions that likely impacted player behavior were omitted from consideration. In basketball, action sequences within possessions are continuous and include actions outside of passing, such as field goals and rebounds. For example, an action sequence for a given possession in a game could be 23-15-FGA2-ORB-7-9-FGM2. However, this dissertation only kept *passing* sequences rather than the full action sequence, which would record the previously described possession as 23-15-7-9, which missed a field goal attempt, an offensive rebound, and a successful two-point field goal.

In STERGM and SAOM, these omitted actions could provide additional underlying information that explains the observed edge lists (e.g., did passing occur between two players primarily when there was an offensive rebound?). This approach also gives an allusion of passing continuity, which is untrue and especially problematic for REM analyses. The utility of REM is its ability to examine relational sequences at a micro-level by leveraging the exact timing and sequence of actions, allowing for the specification of process mechanisms to enable the exploration of emergence (Schecter et al., 2018). Although this was an exploratory assessment of dynamic network methodologies and their applicability to psychological research, the assessment of emergence in these three dynamic network methods is not entirely accurate.

For exploratory purposes, this research additionally treated passing sequences in REM as entirely continuous throughout a game. This enabled the examination of two impractical model terms for basketball teams: PSAB-AY and PSAB-XY. These two passing sequences are not possible within a single possession of basketball game play. These two patterns suggest that the recipient of an action (AB) is not the sender of the next action (AY or XY). However, in basketball game play, if a player is the recipient of a pass, they must be the sender of the next pass or action. Given PSAB-AY and PSAB-XY ignore this assumption entirely, depending on the research question, continuous sequential data that requires recipients to be future senders (e.g., basketball data) may not be the most valid data for conducting research using REM.

Another limitation of this research is regarding data accuracy. Despite an intensive data cleaning and vetting process, the manually collected data were not a perfect match to the data collected by the NBA. Granular passing data (i.e., data used in this dissertation) do not readily exist for public use which inhibits the ability to validate true passing sequences. For example, it is quite possible that players were left out of any given passing sequence or the wrong jersey numbers were recorded in the sequence. Without a way to assess the accuracy of player-by-player passing sequences, the complete accuracy of the data used in this research cannot be established, which limits the analytical power of these methods and their related inferences.

The data vetting process of this dissertation involved assessing the accuracy of player actions (i.e., field goals). This research set an arbitrary cut off for data accuracy: field goal attempts recorded in the manually coded data could not be off by more than 15 field goal attempts relative to the data scraped from Basketball Reference, an online sports website that hosts vast NBA data (www.basketball-reference.com). While majority of the games analyzed were off by one to five field goal attempts, there are nuances in how the NBA records field goal attempts (i.e., any rebound a player makes that is followed by that player releasing the ball, even if the player is not attempting to shoot the ball, is considered a field goal attempt, which a manual coder is more likely to record as a pass or a turnover). This makes it difficult to discern the true accuracy of the manually coded data.

The use of player positions also presented challenge in analytical rigor due to trades made throughout a season. Position data were scraped from Basketball Reference (www.basketball-reference.com), and these data often included duplicate numbers in a team due to trades made during the season. To analyze player data using these network methodologies, you cannot have duplicate node IDs (i.e., player numbers). For that reason, a decision was made to only analyze players that were on a team for majority of the season, which presents inaccuracy in true player positions and, subsequently, related model effects. Moreover, there were instances in which a player in the manually coded data did not exist in the covariate dataset (i.e., a player was incorrectly coded into a sequence), which left these players without a position attribute specified during STERGM analysis. While no effect of player position was found in this research, having more accurate position and player data may have impacted the findings for player position on network behavior.

Another limitation of this research is the model terms selected for analysis. Model terms were selected primarily based on understandability of the terms and practicality of large-scale analysis. For example, evaluating reciprocity is less computationally intensive than assessing more intricate effects, such as a k-star effect where $k = 4$. This term alone would require the model to identify all possible 4-paths for each individual node within each network, of which the dataset contained more than 10,000 separate networks. It is possible that more computationally intensive model terms could explain the observed networks better than the model terms used in this dissertation.

While this research assessed one contextual variable (home versus away status), there are many other variables that can impact game play. One potential contextual variable is travel distance, as partially indicated by home versus away status. For home teams, travel distance would be minimal. However, this research did not consider the travel distance of away teams. Frequent air travel has negative effects on basketball players, such as negatively impacting sleep and nutrition (Huyghe, Scanlan, Dalbo, Calleja-González, 2018). The result of frequent air travel is travel fatigue, which refers to a lack of energy, discomfort, light-headedness, and impatience when traveling across time zones. Players are challenged with adapting to time zones and properly resting before games, which can impact their physical activity, performance, and recovery (Huyghe et al., 2018). Additional contextual variables can include, but are not limited to, a team's coach (who essentially decides on the team's strategy), the level of competition between teams (e.g., perhaps increased competition with an opponent changes game play strategies), personal life circumstances of players (e.g., the loss of a family member), or other affective and cognitive variables (e.g., trust and cohesion amongst players). Without consideration of these contextual variables, findings from this research cannot be properly generalized.

A final limitation of this research is the nature of the teams studied. NBA teams were specifically chosen for this research given the high interdependence between players and the dynamic context in which teams play. While this type of context is appropriate for the research conducted in this dissertation, it limits the generalizability of findings to teams that operate differently than NBA teams (i.e., teams that are less interdependent and/or teams that have stable operating environments). STERGM, SAOM, and REM are still extremely useful methods for examining team processes, specifically relational processes. The NBA data used in this dissertation are rich, nuanced, and provide these analyses a high volume of interaction data. However, less interdependent teams may not provide enough data to match the analytical rigor of the methods used in this research.

Future Research Directions

This study sought to demonstrate the utility of three dynamic network models to guide future research and to highlight the importance of applying rigorous data collection and analytical approaches to understanding team processes. Future research seeking to understand and build theories related to team processes or any other group-level phenomena could consider using these methodologies to enhance data collection efforts and analytical rigor. STERGM, SAOM and REM can help researchers better understand the interrelations between individuals and variables observed to not only explain *what* phenomena occur in groups and teams, but *how* these phenomena unfold over time. Future studies could collect specific relational data based on research questions of interest and apply a theoretically driven approach to selecting appropriate time periods and model terms to better understand underlying behavioral processes of teams.

Another potential endeavor for researchers may be to combine dynamic network models with other analytical approaches to better understand team processes and emergence. Current research on process is typically based on *factor* theories, which confine processes to process *factors* (Braun et al., 2022). Process factors represent summaries of actions and behaviors (e.g., how frequently is an action performed, how well is an action performed) that ignore any temporal or configural elements of behavior (Braun et al., 2022). Researchers can instead leverage *process* theories, which focus on individual actions taken by actors and seek to understand how, when, and why certain actions are taken (Braun et al., 2022).

An analytical approach that is well-suited for studying process theories is computational modeling. Computational modeling is a method that uses mathematical relationships, such as equations and logical if-then statements, to specify how systems change over time (Kozlowski, Chao, Grand, Braun & Kuljanin, 2016). Computational models provide a theory-based method of examining phenomena of interest via mathematics to assess how dynamic processes unfold (Kozlowski et al., 2016). They allow researchers to specify how processes dynamically relate and interact to produce observed actions (Braun et al., 2022).

Using a computational model to assess potential avenues for network behavior based on findings from these dynamic network models could unveil a more nuanced understanding of step-by-step actions taken in STERGM and SAOM (as REM already provides step-by-step actions) and could demonstrate what could happen in these models if actors chose a different course of action than what was observed. For example, a computational model would allow researchers to specify which players were on the court at what time, what actions they took, and what the outcomes were. Specifically, a computational model can leverage the REM results of this research to further understand *when* certain passing sequences are used by *whom* and *how* that relates to observed outcomes. This could further allow researchers to understand key intervention points in team processes to enable a more efficient and effective assessment of how interventions are performing, and to further understand both intended and unintended consequences of interventions (Braun et al., 2022). Moreover, computational models allow researchers to program an infinite number of variables, including contextual variables, which would help assess a team's entire system versus just observing the data collected.

Future research also could apply all three methods used in this study to further address underlying processes for given research questions. Each method assessed in this dissertation has unique functionality and purpose. STERGM can be used in research aimed to assess how individuals, their relations and their covariates impact relationship formation and persistence over time. SAOM can be used in research intended to additionally assess how network structure impacts individual behavior to further understand the interrelatedness of network and individual behavior. REM can be used in research intended to focus on the sequencing, patterns, timing, and likelihood of social interactions to focus on the nuanced behavioral sequences that drive future behavior. For researchers seeking to explore the intersection of network structure, individual behavior, and action sequences, all three methods can provide unique yet complimentary perspectives on individual and team behavior. While each research method provides a unique way to explore and analyze team data, researchers would benefit from leveraging the various perspectives provided by each method to address their research questions more holistically.

Future researchers could also assess more contextual factors to understand how they enable or constrain behavior. This research focused on the relationship between home versus away status and player behavior. However, many other contextual variables exist for these teams and each team has a unique set of contextual variables that impact behavior. The I-P-O model considers context as an input that influences team processes (Hackman, 1987). For example, the interdependence of work is an antecedent of psychological safety, or the shared belief that team members can take interpersonal risks without fear of backlash (Edmondson, 1999). Interdependence is just one contextual variable that can impact team processes, and future research on team processes could incorporate more contextual variables to better understand team phenomena.

Conclusion

This study aimed to explore three dynamic network methods (STERGM, SAOM, REM) that can advance the study of team processes using NBA basketball teams. This research highlighted the unique capabilities of each dynamic network method in assessing team processes and encourages future team process researchers to use these methods as they require methodological and analytical rigor that team process research is lacking today. STERGM is well suited for examining how relationships form and are maintained over time; SAOM is well suited to further examine the interrelatedness of network and individual behavior; REM is well suited to understand nuanced behavioral sequences that drive future behavior.

This dissertation discovered that for NBA basketball teams, mutual passing is the most prevalent passing behavior of those examined, followed by transitive passing. Universally for NBA teams, players are likely to pass back to those who pass to them (mutual ties), and it is also likely that triangular passing relations form between three players (transitive ties). Passing behavior was found to link to performance based on STERGM analyses such that teams that formed more mutual and transitive passing relations were more likely to win games. Player position and player scoring were not found to have strong effects on relational behaviors within teams, nor was home versus away status found to impact passing relations. Future research is encouraged to assess team process at a fine-grained level and consider the team system, including inputs and context, to identify how team processes link to team outcomes.

Conceptualizing teams as networks forces researchers to take a relation-based approach to analyzing teams and to treat team member behaviors as interdependent, as they are, by definition, within teams (Humphrey & Aime, 2014). Network analyses assess how the intersection of relations within groups enable or constrain behavior within a group's context, focusing on *who* is related to *whom* in a network (Borgatti & Ofem, 2010). Dynamic network analyses incorporate time to explore *when* certain individuals interact and when their behavior occurs, which brings researchers closer to understanding *how* actions impact outcomes, as required of process theories (Braun et al., 2022).

The field of industrial and organizational (I-O) psychology is dedicated to addressing workplace issues to improve how organizations operate with the intent of enhancing the lives of the people that interact with organizations (SIOP, 2022; Watts, Gray & Medeiros, 2021). Organizations are multilevel and dynamic, making them inherently complex and comprised of infinite interaction processes (Katz & Kahn, 1996; Kozlowski & Klein, 2000). For I-O psychologists to continue impacting organizations by identifying interventions to enhance organizational processes, it is critical that our research methods and analytical approaches match the complexity and rigor demanded of organizational systems. Taking a dynamic network approach and a process theory lens to studying teams within organizations can further advance the field of I-O psychology by learning the complex nature of behavioral interactions and processes of teams and enabling researchers to better identify optimal interventions for improving processes and related outcomes for organizations.

References

Anderson, N., & Thomas, H. D. (1996). Work group socialization. *Handbook of work group psychology*, *423*, 450.

Beal, D. J., Cohen, R. R., Burke, M. J., & McLendon, C. L. (2003). Cohesion and performance in groups: a meta-analytic clarification of construct relations. *Journal of applied psychology*, *88*(6), 989.

Beckstead, J. W. (2002). Using hierarchical cluster analysis in nursing research. *Western Journal of Nursing Research*, 24(3), 307-319.

Bell, S. T., Villado, A. J., Lukasik, M. A., Belau, L., & Briggs, A. L. (2011). Getting specific about demographic diversity variable and team performance relationships: A meta-analysis. *Journal of management*, *37*(3), 709-743.

Block, P., Koskinen, J., Hollway, J., Steglich, C., & Stadtfeld, C. (2018). Change we can believe in: Comparing longitudinal network models on consistency, interpretability and predictive power. *Social Networks, 52*, 180-191.

Borgatti, S., & Ofem, B. (2010). Overview: Social network theory and analysis. *Social Network Theory and Educational Change,* 17-30.

Boudreaux, C. J., Sanders, S. D., & Walia, B. (2017). A natural experiment to determine the crowd effect upon home court advantage. *Journal of Sports Economics*, *18*(7), 737-749.

Brandenberger, L. (2018). *rem: Relational Event Models*. R package version 1.3.1.

Brandenberger, L. (2020). Interdependencies in Conflict Dynamics: Analyzing Endogenous Patterns in Conflict Event Data Using Relational Event Models. In *Computational Conflict Research* (pp. 67-80). Springer, Cham.

Bratchell, N. (1989). Cluster analysis. Chemometrics and Intelligent Laboratory Systems, 6, 105–125.

Braun, M. T., Kuljanin, G., & DeShon, R. P. (2018). Special considerations for the acquisition and wrangling of big data. *Organizational Research Methods*, *21*(3), 633-659.

Braun, M. T., Kuljanin, G., Grand, J. A., Kozlowski, S. W., & Chao, G. T. (2022). The power of process theories to better understand and detect consequences of organizational interventions. *Industrial and Organizational Psychology*, *15*(1), 99-104.

Burke, C. S., Stagl, K. C., Salas, E., Pierce, L., & Kendall, D. (2006). Understanding team adaptation: A conceptual analysis and model. *Journal of Applied Psychology*, *91*(6), 1189.

Butts, C. T. (2008). 4. A Relational Event Framework for Social Action. *Sociological Methodology*, *38*(1), 155-200.

Butts, C. T. (2015). Relational Event Models. URL https://cran.r-project.org/web/packages/relevent/relevent.pdf

Butts, C. T. (2020). Tools for Social Network Analysis. URL http://statnet.org

Chen, G., & Klimoski, R. J. (2003). The impact of expectations on newcomer performance in teams as mediated by work characteristics, social exchanges, and empowerment. *Academy of management Journal*, *46*(5), 591-607.

Chrobot-Mason, D., Gerbasi, A., & Cullen-Lester, K. L. (2016). Predicting leadership relationships: The importance of collective identity. *The Leadership Quarterly*, *27*(2), 298-311.

Costa, A. C., Roe, R. A., & Taillieu, T. (2001). Trust within teams: The relation with performance effectiveness. European journal of work and organizational psychology, 10(3), 225-244.

Czarna, A. Z., Leifeld, P., Śmieja, M., Dufner, M., & Salovey, P. (2016). Do narcissism and emotional intelligence win us friends? Modeling dynamics of peer popularity using inferential network analysis. *Personality and Social Psychology Bulletin*, *42*(11), 1588-1599.

De Wit, F. R., Greer, L. L., & Jehn, K. A. (2012). The paradox of intragroup conflict: a meta-analysis. *Journal of applied psychology*, *97*(2), 360.

Dishop, C. R., Braun, M. T., Kuljanin, G., & DeShon, R. P. (2020). Thinking longitudinal: a framework for scientific inferences with temporal data. In *Handbook on the Temporal Dynamics of Organizational Behavior*. Edward Elgar Publishing.

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative science quarterly*, *44*(2), 350-383.

Entine, O. & Small, D. S. (2008). The role of rest in the NBA home-court advantage. *Journal of Quantitative Analysis in Sports, 4*(2).

Epskamp, S., Cramer, A. O. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometrics data. *Journal of Statistical Software, 48*(4), 1-18.

Erdös, P., & Rényi, A. (1960). On the evolution of random graphs. *Publ. Math. Inst. Hung. Acad. Sci*, *5*(1), 17-60.

Feldman, D. C. (1984). The development and enforcement of group norms. *Academy of management review*, *9*(1), 47-53.

Frank, O. & Strauss, D. (1986). Markov graphs. *Journal of the American Statistical Association, 81*(395), 832-842.

Fritz, C., Lebacher, M., & Kauermann, G. (2020). Tempus volat, hora fugit: A survey of tie-oriented dynamic network models in discrete and continuous time. *Statistica Neerlandica*, *74*(3), 275-299.

Gerald, B. (2018). A brief review of independent, dependent and one sample t-test. *International journal of applied mathematics and theoretical physics*, *4*(2), 50-54.

Gilbert, E. N. (1959). Random graphs. *The Annals of Mathematical Statistics*, *30*(4), 1141-1144.

Goldenberg, A., Zheng, A. X., Fienberg, S. E., & Airoldi, E. M. (2010). A survey of statistical network models.

Grand, J. A., Braun, M. T., Kuljanin, G., Kozlowski, S. W., & Chao, G. T. (2016). The dynamics of team cognition: A process-oriented theory of knowledge emergence in teams. *Journal of Applied Psychology*, *101*(10), 1353.

Gully, S. M., Devine, D. J., & Whitney, D. J. (1995). A meta-analysis of cohesion and performance: Effects of level of analysis and task interdependence. *Small group research*, *26*(4), 497-520.

Gully, S. M., Incalcaterra, K. A., Joshi, A., & Beaubien, J. M. (2002). A meta-analysis of team-efficacy, potency, and performance: interdependence and level of analysis as moderators of observed relationships. *Journal of applied psychology*, *87*(5), 819.

Guo, F., Hanneke, S., Fu, W., & Xing, E. P. (2007). Recovering temporally rewiring networks: A model-based approach. In Proceedings of the 24th international conference on Machine learning (pp. 321-328).

Hackman, J. R. (1987). The design of work teams. In JW Lorsch (Ed.), Handbook of Organizational Behavior, Englewood Cliffs, NJ: Prentice-Hall.

Handcock, M., Hunter, D., Butts, C., Goodreau, S., Krivitsky, P., & Morris, M. (2018). Ergm: Fit, simulate and diagnose exponential-family models for networks. The Statnet Project (http://www.statnet.org). R.

Hanneke, S., Fu, W., & Xing, E. P. (2010). Discrete temporal models of social networks. *Electronic Journal of Statistics*, *4*, 585-605.

Hays-Thomas, R. (2016). *Managing workplace diversity and inclusion: A psychological perspective*. Routledge.

Herring, C. (2009). Does diversity pay?: Race, gender, and the business case for diversity. *American sociological review*, *74*(2), 208-224.

Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. (1997). The emerging conceptualization of

Holland, P. W., & Leinhardt, S. (1981). An exponential family of probability distributions for directed graphs. *Journal of the american Statistical association*, *76*(373), 33-50.

Honaker, J., King, G., & Blackwell, M. (2011). Amelia II: A program for missing data. *Journal of Statistical Software*, *45*(7), 1-47. URL http://www.jstatsoft.org/v45/i07/.

Hoobler, J. M., Masterson, C. R., Nkomo, S. M., & Michel, E. J. (2016). The business case for women leaders: Meta-analysis, research critique, and path forward. *Journal of Management*, 1-27.

http://www.rstudio.com/. Robins, G., Snijders, T., Wang, P., Handcock, M., & Pattison, P. (2007). Recent developments in exponential random graph (p*) models for social networks. *Social networks*, *29*(2), 192-215.

Humphrey, S. E., & Aime, F. (2014). Team microdynamics: Toward an organizing approach to teamwork. *The Academy of Management Annals*, *8*(1), 443-503.

Hunt, V., Layton, D., & Prince, S. (2015). Diversity matters. *Retrieved from:* https://www.mckinsey.com/business-functions/organization/our-insights/why-diversity-matters

Hunter, D. R., & Handcock, M. S. (2006). Inference in curved exponential family models for networks. *Journal of Computational and Graphical Statistics*, *15*(3), 565-583.

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in organizations: From input-process-output models to IMOI models. *Annu. Rev. Psychol.*, *56*, 517-543.

Jarvenpaa, S. L., Knoll, K., & Leidner, D. E. (1998). Is anybody out there? Antecedents of trust in global virtual teams. *Journal of management information systems*, *14*(4), 29-64.

Kalish, Y. (2020). Stoachastic actor-oriented models for the co-evolution of networks and behavior: An introduction and tutorial. *Organizational Research Methods, 23*(3), 511-534.

Kalish, Y., & Luria, G. (2016). Leadership emergence over time in short-lived groups: Integrating expectations states theory with temporal person-perception and self-serving bias. *Journal of Applied Psychology*, *101*(10), 1474.

Karell, D. (2018). *Stochastic Actor-Oriented Models and "Change we can believe in: Comparing longitudinal network models on consistency, interpretability and predictive power."* Presentation, Princeton.

Katz, D., & Kahn, R.L. (1966). The social psychology of organizations. Wiley.

Kim, T., McFee, E., Olguin, D. O., Waber, B., & Pentland, A. S. (2012). Sociometric badges: Using sensor technology to capture new forms of collaboration. *Journal of Organizational Behavior*, *33*(3), 412-427.

Knoke, D., & Yang, S. (2008). Network fundamentals. *Social network analysis*, (154), 3-14.

Kozlowski, S. W. J. (2015). Advancing research on team process dynamics: Theoretical, methodological, and measurement considerations. *Organizational Psychology Review, 5*(4), 270-299.

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest*, *7,* 77–124.

Kozlowski, S. W., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes

Kozlowski, S. W., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2013). Advancing multilevel research design: Capturing the dynamics of emergence. *Organizational Research Methods*, *16*(4), 581-615.

Kozlowski, S. W., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2016). Capturing the multilevel dynamics of emergence: Computational modeling, simulation, and virtual experimentation. *Organizational Psychology Review*, *6*(1), 3-33.

Krivitsky, P. N., & Handcock, M. S. (2014). A separable model for dynamic networks. *Journal of the Royal Statistical Society. Series B, Statistical Methodology*, *76*(1), 29.

Leenders, R. T. A., Contractor, N. S., & DeChurch, L. A. (2016). Once upon a time: Understanding team processes as relational event networks. *Organizational Psychology Review*, *6*(1), 92-115.

Leifeld, P., & Cranmer, S. J. (2015). A theoretical and empirical comparison of the temporal exponential random graph model and the stochastic actor-oriented model. *arXiv preprint arXiv:1506.06696*.

Leifeld, P., Cranmer, S. J., & Desmarais, B. A. (2018). Temporal exponential random graph models with btergm: Estimation and bootstrap confidence intervals. *Journal of Statistical Software*, *83*(6).

LePine, J. A., Piccolo, R. F., Jackson, C. L., Mathieu, J. E., & Saul, J. R. (2008). A meta-analysis of teamwork processes: tests of a multidimensional model and relationships with team effectiveness criteria. *Personnel Psychology*, *61*(2), 273-307.

Lubbers, M. J., Molina, J. L., Lerner, J., Brandes, U., Ávila, J., & McCarty, C. (2010). Longitudinal analysis of personal networks. The case of Argentinean migrants in Spain. *Social Networks*, *32*(1), 91-104.

Lusher, D., Kremer, P., & Robins, G. (2014). Cooperative and competitive structures of trust relations in teams. *Small group research*, *45*(1), 3-36.

Lusher, D., Robins, G., & Kremer, P. (2010). The application of social network analysis to team sports. *Measurement in physical education and exercise science*, *14*(4), 211-224.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. *Academy of management review*, *26*(3), 356-376.

Mathieu, J. E., Hollenbeck, J. R., van Knippenberg, D., & Ilgen, D. R. (2017). A century of work in the Journal of Applied Psychology. *Journal of Applied Psychology, 102*(3), 452-467.

Mathieu, J. E., Kukenberger, M. R., D'innocenzo, L., & Reilly, G. (2015). Modeling reciprocal team cohesion–performance relationships, as impacted by shared leadership and members' competence. *Journal of Applied Psychology*, *100*(3), 713.

Mathieu, J., Maynard, M. T., Rapp, T., & Gilson, L. (2008). Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future. *Journal of management*, *34*(3), 410-476.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, *27*(1), 415-444.

Mesmer-Magnus, J. R., & DeChurch, L. A. (2009). Information sharing and team performance: A meta-analysis. *Journal of applied psychology*, *94*(2), 535.

Mitchell, T. R., & James, L. R. (2001). Building better theory: Time and the specification of when things happen. *Academy of Management Review, 26*(4), 530-547.

Mizruchi, M. S. (1985). Local sports teams and celebration of community: A comparative analysis of the home advantage. *The Sociological Quarterly, 26*(4), 507-518.

Morris, M., Krivitsky, P. N., Handcock, M. S., Butts, C. T., Hunter, D. R., Goodreau, S. M., & Bender-deMoll, S. (2019). Temporal exponential random graph models (TERGMs) for dynamic network modeling in statnet. statnet.org/Workshops/tergm_tutorial.html

Newman, D. A. (2003). Longitudinal modeling with randomly and systematically missing data: A simulation of ad hoc, maximum likelihood, and multiple imputation techniques. *Organizational Research Methods, 6*(30, 328-362.

Pedersen, T. L. (2020). A tidy API for graph manipulation. URL https://cran.r-project.org/web/packages/tidygraph/tidygraph.pdf

Perkins, K. (2017). *Does home court advantage exist in the National Basketball Association between conferences?* ProQuest Dissertations Publishing.

Pilny, A., Schecter, A., Poole, M. S., & Contractor, N. (2016). An illustration of the relational event model to analyze group interaction processes. *Group Dynamics: Theory, Research, and Practice, 20*(3), 181-195.

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of management*, *36*(1), 94-120.

Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *885*(879), 10-1037.

R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Revelle, W. (2020). psych: Procedures for psychological, psychometric, and personality research. URL https://CRAN.R-project.org/package=psych

Ripley, R. M., Snijders, T. A., Boda, Z., Vörös, A., & Preciado, P. (2021). Manual for RSIENA. *University of Oxford, Department of Statistics, Nuffield College*, *1*, *R package version 1.2-23. https://www.cran.r-project.org/web/packages/RSiena/.*

Robins, G., & Pattison, P. (2001). Random graph models for temporal processes in social networks. *Journal of Mathematical Sociology, 25*(1), 5-41.

RStudio Team (2016). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA. URL http://www.rstudio.com/

Ruef, M., Aldrich, H. E., & Carter, N. M. (2003). The structure of founding teams: Homophily, strong ties, and isolation among US entrepreneurs. *American sociological review*, 195-222.

Salas, E., Grossman, R., Hughes, A. M., & Coultas, C. W. (2015). Measuring team cohesion: Observations from the science. *Human factors*, *57*(3), 365-374.

Schaefer, D. R. (2016). *An introduction to stochastic actor-oriented models (aka SIENA).* [PowerPoint slides]. SlideShare. https://www.slideshare.net/dnac2017/13-an-introduction-to-stochastic-actororiented-models-2016

Schaefer, D. R. (2019). *An introduction to stochastic actor-oriented models (SAOM or SIENA).* [PowerPoint slides]. SlideShare.

https://www.slideshare.net/dnac2017/22-an-introduction-to-stochastic-actororiented-models-saom-or-siena?from_action=save

Schaefer, D. R., & Marcum, C. S. (2017). Modeling network dynamics. In *The Oxford Handbook of Social Networks*.

Schecter, A., & Contractor, N. (2017). Understanding and assessing collaborative processes through relational events. In *Innovative Assessment of Collaboration*, 223-231.

Schecter, A., Pilny, A., Leung, A., Poole, M. S., & Contractor, N. (2017). Step by step: Capturing the dynamics of work team process through relational event sequences. *Journal of Organizational Behavior*, *39*(9), 1163-1181.

Snijders, T. A. (1996). Stochastic actor-oriented models for network change. *Journal of mathematical sociology*, *21*(1-2), 149-172.

Snijders, T. A. (2016). Stochastic actor-oriented models for network dynamics.

Snijders, T. A., Van de Bunt, G. G., & Steglich, C. E. (2010). Introduction to stochastic actor-based models for network dynamics. *Social networks*, *32*(1), 44-60.

Society of Industrial-Organizational Psychology (2022). *About the society for industrial and organizational psychology*. Retrieved April 30, 2022 from http://www.siop.org/About- SIOP.

Spector, P. E. (1994). Using self-report questionnaires in OB research: A comment on the use of a controversial method. *Journal of organizational behavior*, *15*(5), 385-392.

Statnet Development Team (2021, June 29). *Temporal Exponential Random Graph Models (TERGMs) for dynamic network modeling in statnet.* statnet.org.

https://statnet.org/Workshops/tergm/tergm_tutorial.html#Statistical_Modeling_with_tergm

Tuckman, B. W. (1965). Developmental sequence in small groups. *Psychological bulletin*, *63*(6), 384.

Ward, J. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association, 58,* 236-244.

Warner, S., Bowers, M. T., & Dixon, M. A. (2012). Team dynamics: A social network perspective. *Journal of Sport Management*, *26*(1), 53-66.

Watts, L. L., Gray, B. E., & Medeiros, K. E. (2021). Side effects associated with organizational interventions: A perspective. Industrial and Organizational Psychology: Perspectives on Science and Practice, 15(1), 76–94.

Weinfurt, K. P. (1995). Multivariate analysis of variance. In L. G. Grimm & P. R. Yarnold (Eds.), *Reading and understanding multivariate statistics* (pp. 245–276). American Psychological Association.

Wickham, H. (2020). Easily Harvest (Scrape) Web Pages. URL https://rvest.tidyverse.org/

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, **4**(43), 1686. doi: 10.21105/joss.01686.

Appendix

Supplemental Logistic Regression Output for STERGM Model 1

	$\boldsymbol{\beta}$	SE	Odds Ratio (Exp($\boldsymbol{\beta}$))	95% CI
Intercept	0.504*	0.260	1.656	[0.995, 2.756]
Form~ Edges	0.367***	0.260	1.443	[1.105, 1.884]
Form ~ Mutual Ties	0.200**	0.136	1.221	[1.004, 1.486]
Form ~ Transitive Ties	0.491***	0.100	1.633	[1.182, 2.257]
Persist ~ Edges	0.020	0.166	1.020	[0.987, 1.055]
Persist ~ Mutual Ties	0.010	0.008	1.010	[0.994, 1.026]
Persist ~ Transitive Ties	-0.017	0.013	0.983	[0.958, 1.008]

*p < .10, ** p< .05, ***p < .01