Team Coordination and Game-Based Interaction Networks in Soccer: Analyzing Team Coordination Properties of Elite Soccer Teams Based on Intra-Team Passes Patterns

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TEAM COORDINATION AND GAME-BASED INTERACTION NETWORKS IN SOCCER: ANALYZING TEAM COORDINATION PROPERTIES OF ELITE SOCCER TEAMS BASED ON INTRA-TEAM PASSES PATTERNS

By

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I dedicate my dissertation to my family.
אתם האבנים הגדולות של החיים. אני אוהב כל אחד ואחת מכם

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ABSTRACT

Ecological dynamics perspective studies in sport assume that repeated interactions among teammates in real-time activities yield compound variables that specify behavioral characteristics of teams (Araújo & Bourbousson, 2016). Based on the principles of the Social Network Analysis (SNA) approach, the Game-Based Interaction Networks (GBIN) method is used to quantify the passing synergistic proprieties of team ball sports during live matches. The current study was aimed at uncovering the unobserved collective patterns that distinguish among teams at different stages of expertise, while investigating the consistency of the structured networks over a prolonged time of one competitive season. The study included 66 soccer matches from the 2018/2019 season, from the La-Liga Spanish league, English Premier League, and German Bundesliga. Deploying a standardized taxonomy of sport expertise (Swann et al., 2015), one-way MANOVAs revealed that world-class elite teams were more likely to maintain higher density ratings, lower centrality ratings, and superior performance outcomes when playing against competitive-elite teams. Multiple linear regression analyses were applied to test the predictive power of the coefficient factors on each performance criterion. The results of the multiple regression analyses revealed that both, average clustering coefficient and weighted out-degree centrality, significantly accounted for 33% of the variance in overall number of passes, and that average clustering coefficient accounted for 23% in the variance of passes accuracy percentage, 9% of the variability in goals allowed, approximately 17% of the variance in goals conceded, and nearly 13% of the variability in expected goals. Moreover, one-way MANOVAs revealed that world-class elite teams presented relatively similar indices when playing against each other. Additional one-way MANOVAs revealed similar network topology among the competitive-elite teams. Visual network configurations support the observations of these results. Overall, the findings in the current study call for further applied and theoretical applications endorsing the GBIN method as an operational definition of team coordination in team sports. Limitations, future directions, and implications are discussed in detail.

Key Words: Ecological Dynamics Perspective, Team Coordination, Game-Based Interaction Networks, Soccer, Sport Psychology

CHAPTER ONE

LITERATURE REVIEW

Team Coordination

Even though teams are used in many contexts, when asked to describe a team, many refer to the domain of sport (McNeese, Cooke, Feedele, & Gray, 2015). While some scholars use the terms groups and team interchangeably, a team is considered as a unique type of group (Blickensderfer, Reynolds, Salas, & Cannon-Bowers, 2010). The emphasis of the group is on the people who interact with each other and share common aspects. The defining features of people who interact with each other and perceive themselves as a 'team' include at least one shared goal, constructed relationship, and distinctive roles (Bourbousson, Poizat, Saury, & Seve, 2010). Essentially, team sport members operate under dynamic, complex, and uncertain constraints, whereby, they must be tightly coordinated with each other to achieve specific performance goals (Araújo & Davids, 2016). Despite the prevalence of teams in the exercise and sport contexts, there is relatively little research involving teams' mechanisms compared with other psychological topics in our field (Eys, Bruner, & Matrin, 2019). Thus, exploring synthesizing team coordination factors may provide further insights regarding a salient competitive advantage.

According to Steiner (1972), the potential productivity of teams may be inhibited due to two faulty processes: *motivation losses* and *coordination losses*. The motivation decrement is attributed primarily to social factors such as the phenomenon of social loafing. For instance, Ringelmann (1913, cited in Kravitz & Martin, 1986) observed rope pulling tasks, and found that as the number of people in the group increased, each individual tended to employ a diminished force exertion, resulting in overall deteriorated performance. However, a more recent investigation by Kravitz and Martin (1986) concluded that Ringelmann ascribed the faulty processes also to coordination losses, such as the lack of synchronized muscular contraction among team members. Considering the key principles of coordination, Eccles (2010) related to the noun '*coordination'* as both a process and an outcome. Concerning sports teams, coordination as an outcome refers to the results of the combined efforts of the team members towards the accomplishment of shared goal. Conversely, coordination as a process designates the jointly behavioral patterns that are generated by team members in the aim of achieving effective results (i.e., coordination as an outcome). In this context, the actions of each team member, individually, must be integrated with the team collectively to meet the demands of the task (Bourbousson et al., 2010).

Team Cohesion

The development and maintenance of sport teams are rooted on *team cohesion* that was defined as "a dynamic process that is reflected in the tendency of a group to stick together and remain united in the pursuit of its instrumental objectives and/or for the satisfaction of member affective needs" (Carron, Brawley, & Widmeyer, 1998, p. 213). While the framework of investigating team processes in sport is geared heavily towards social factors, task aspects must also be considered since they occur in every team (Eccles & Tenenbaum, 2004). Therefore, the two constructs that underpin team cohesion refers to social and task forces. Specifically, *social cohesion* targets interpersonal relationships in the team, while *task cohesion* pertains to the perception of how teammates work together towards the achievement of common goals (Carron et al., 1998). The social and task cohesion constructs have been conceptualized as orthogonal, meaning that teams may be high in one type and low in another, as well as high or low in both types of cohesion at the same time (Filho, 2018).

Martens and Peterson (1971) executed one of the earliest empirical studies that examined the type of relationship between cohesion and performance in sport. The authors found that there is a circular relationship between the two variables; increased cohesion leads to superior performance, and as the team performance improves, the team tends to be more cohesive. Many studies supported this type of relationship between cohesion and performance in different sports (Warner, Bowers, & Dixon, 2012). This literature was amalgamated by retrospective meta-analysis (Filho, Dobersek, Gershgoren, Becker, & Tenenbaum, 2014), which revealed a moderate relationship between cohesion and performance ($r = 0.34$, $p < 0.01$). Notably, when analyzing the relationship between the two constructs of cohesion and performance, a stronger effect size was noted in the relationship between task cohesion and performance ($r = 0.45$, $p < 0.01$) than the relationship between social cohesion and performance ($r = 0.11$, $p < 0.01$), suggesting that task cohesion is a more prominent factor contributing to team performance. Although the cohesion-performance relationship has been identified, Carron et al. (2002) argued that scholars must examine the potential mediators that explain the underlying mechanism between cohesion and performance. At this stage, the only measure that was identified as a mediator in the cohesion-performance relationship is *collective efficacy*, which is defined as "a group's shared belief in their conjoint capabilities to organize and execute the courses of action required to produce given levels of attainments" (Bandura, 1997, p. 476)." While the mediating variable of collective efficacy is associated with the orientation of social cohesion (Warner et al., 2012), there is a need for theoretical principles and empirical data that concentrate on the mechanisms which account for team members operating together (i.e., task-cohesion) towards the achievement of successful performance (Vilar, Araújo, Davids, & Button, 2012).

Theoretical Perspectives on Coordinated Behaviors of Sport Teams

Three main theoretical frameworks were proposed to capture the emergence of coordination in team sports: (1) The social-cognitive, (2) the enactive, and (3) the ecological dynamics (Araújo & Bourbousson, 2016).

The Socio-Cognitive Perspective

Driven by concepts from social cognition and I/O, Eccles and Tenenbaum (2004) laid the foundations for investigating the *socio-cognitive perspective* of team coordination in the arena of sport and exercise psychology. A central tenet has been devoted to the understating of shared knowledge among teammates. The notion of a team mental model (TMM) was developed to account for performance differences among teams and refers to "an organized understanding of relevant knowledge that is shared by team members" (Mohammed & Dumville, 2001, p. 89). Specifically, to perform their potential, teammates must know about each other's characteristics, possess *task-knowledge* (i.e., knowledge of the tasks to be accomplished by the team) and *team-knowledge* (i.e., knowledge of how teamwork should be accomplished; Filho & Tenenbaum, in press). Moreover, TMM conceptualizes the understanding of how teams operate in contexts that are complex, dynamic, and uncertain (Cannon-Bowers & Salas, 1990). Correspondingly, TMM has been investigated in diverse contexts in the last two decades, including the military (e.g., Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000), medicine (e.g., McComb & Simpson, 2014), artificial intelligence (e.g., Scheutz, DeLoach, & Adams, 2017), and sport and exercise (e.g., Gray, Cooke, McNeese, & McNabb, 2017).

The processes of anticipating and predicting the behaviors of one's teammates are vital to the overall coordination and performance of a team (Tannenbaum, Salas, & Cannon-Bowers, 1996). When sharing similar anticipatory actions, better decision-making is more likely to occur, especially in expert teams (Reimer, Park, & Hinsz, 2006). Then, actions can be coordinated. For example, a recent study integrated the methodology of temporal occlusion paradigm and joint decision-making in baseball (Gray et al., 2017); professional players were required to coordinate their actions in minimum time while watching 70 game scenarios. The results showed that teammates who played out of their positions (the scrambled teammates' group) made quicker and more coordinated decisions rather than a group of non-teammates who played in their original positions. The authors explained the superiority of the scrambled teammates' group due to knowledge about their teammates and teammates' action capabilities (Gray et al., 2017). In these teams, the players are not necessarily relying on more concepts but rather express the mutual representations in multiple ways, which allows addressing barriers and facilitators of performance (Carely, 1997).

Expert teams develop shared understanding through coordination processes which occur before, during, and after the teams' operations (Eccles & Tenenbaum, 2004). Prior to the performance, teams can engage in various behaviors, such as planning, sharing collective goals, allocating roles, and tactical understanding. The preparatory behaviors facilitate information processing that enable teammates to generate shared underlying schema that can be expressed later in the competitive environment. According to Eccles and Tenenbaum (2004), teammates also produce shared knowledge during the execution of the task. When practicing together, teammates improve their abilities to identify the "habits, preferences, and idiosyncrasies of their follow members" (p. 552), which ultimately, facilitates the interpretation of various situational probabilities. Expert players develop memory adaptations, which enable them to react flexibly to rapid changes in the environment. For example, compared with the awareness patterns of novice basketball team players, expert players heeded less on each other during a match, which can be interpreted as a parsimonious intra-team behavior (Bourbousson, R'Kiouak, & Eccles, 2015). Along with achieving in-process implicit coordination, teammates can operate through explicit coordination mode; the latter refers to increased deliberate communication among teammates that is more likely to occur when the implicit coordination processes are not well-established (McNeese et al., 2015). Lastly, teammates engage in post-process coordination that comprises metacognition behaviors pertaining to the team performance, such as verbal discussions and viewing of previous performance films (Eccles & Tenenbaum, 2004). On a similar vein, teams that were engaged in monitoring the task execution, and then determined their future strategies, showed improved performance compared to teams who did not take part in these processes (Rasker, Post, & Schraagen, 2000).

Researchers investigating socio-cognitive processes utilized methods that were based mostly on the *collective* and *holistic techniques* (Cooke, Salas, Cannon-Bowers, & Stout, 2000). The collective approach captures the knowledge of the individual team members, and then integrates this information, while the holistic approach concentrates on the team-level processes, such as communication, situation assessment, and coordination (McNeese et al., 2015). New methods to explore team cognition concepts in sport include the utilization of *eye tracking* (Wildman, Salas, & Scott, 2014) and *hyper brain networks* (Filho & Tenenbaum, in press). The eye tracking method enables monitoring of the gaze behavior which the individual and team members attend to during an execution of a task (Feldman, Lum, Sims, Smith-Jentsch, & Lagattuta, 2008). Another advancement in measuring TMM is using hyper brain networks via the establishment of neuroimaging analysis during interactive tasks between teammates, such as cooperative juggling (Filho & Tenenbaum, in press).

Although the shared knowledge hypothesis is recognized as a precursor condition for the existence of team coordination, it is claimed to be more conceptually reformulated and defined more precisely (Mohammed & Dumville, 2001). Hitherto it is challenging to prove that representations exist beyond the boundaries of an individual organism and can be somehow shared with others (Silva, Garganta, Araújo, Davids, & Aguiar, 2013). Furthermore, the understanding of team cognition has been limited by the methodologies used to study it. Most of the TMM measures were based on individual passive responses that resulted from the elicitation and aggregation methods, and allegedly misconstrued the concept of TMM (Converse, Cannon-Bowers, & Salas, 1993). To fully capture the actions that occur during sport, McNeese and colleagues (2015) urged that studying team cognition in sport must include a combination of both the shared knowledge and dynamical approaches.

The Enactive Perspective

An additional theoretical and methodological framework, which aimed at capturing team coordination in sport is the *enactive approach*. Cognitions are expressed with respect to a phenomenological approach, which involves verbal descriptions of individuals in their real-time activity (Araújo & Bourbousson, 2016). The assumption is that through assigning meaning of the lived experience in a simultaneous task, it provides an exploration of whether each team member is more or less attuned to environmental information (Gesbert, Durny, & Hauw, 2017). The meaningful discrete units may be revealed through physical actions, communicative exchanges, interpretations, or feelings (Bourbousson, et al., 2010). For instance, a previous study showed that Olympic rowers coordinated their actions based on the variations in the boat speed rather than taking each other into account (Millar, Oldham, & Renshaw, 2013).

To explore the ongoing team coordination in naturalistic environments, the enactive approach utilizes retrospective phenomenological interview techniques (Gesbert et al., 2017). First, following the competition, athletes watch video recordings and verbalize their “involvement in the situation” (Feigean, R'kiouak, Seiler, & Bourbousson, 2018). The second step includes a procedure called the ‘synchronization of the participants' courses of action,’ which the meaningful subjective experiences are connected to establish a collective unit (Araújo & Bourbousson, 2016). The identification of collective units facilitates the characterization of the relationship between individual courses of action in specific sport situations. For example, elite soccer players were not aware of their teammates as they coordinated to collectively recover the ball, but rather they adjusted to each other through the behavior of the opponent ball carrier (Gesbert et al., 2017). Consequently, the enactive approach provides a qualitative description of how coordination is formed, stabilized, and demolished during an unfolding joint action (Araújo & Bourbousson, 2016).

The enactive approach comprises descriptions of team activity, which are grounded by the first-person point of view (Feigean et al., 2018). However, it is vulnerable to some extent to the accuracy of the subjective experience of the organism, and it is susceptible to biases faced by the researcher when interpreting the descriptive data (Araújo & Bourbousson, 2016). Moreover, the theoretical framework lacks explanations pertaining to the nested of subjective experiences into dynamical behavioral patterns. Furthermore, the scope of verbal descriptions is limited to conscious aspects of the situation, which completely distorts the notion of team cognition (Feigean et al., 2018). Concerning these limitations, analyzing the physical coordination patterns within the team has the potential to show further coordinating elements that are not controlled only by individual’s attention, and are more directly related to the concept of team cognition in sport (McNeese et al., 2015).

The Ecological Dynamics Perspective

The third approach to explore team coordination relies on the framework of *ecological dynamics*, which assumes that observable intrateam patterns at the behavioral level are “sufficient to reveal the key environmental constraints that underlie team coordination” (Feigean et al., 2018, p. 155). That is, the interaction among players can yield compound variables that specify behavioral patterns in naturalistic environments (Araújo & Bourbousson, 2016). In this respect, the emphasis is on describing and examining dynamical principles among units that are connected not only mechanically, but also informationally (Araújo & Bourbousson, 2016). Since dynamics applies to the way a system changes or behaves over time, it is essential to consider that changes are not limited by individual activity, but also result by social processes (Silva et al., 2016). Therefore, specific informational constraints include players’ characteristics, team strategy, and coaches’ instructions, which impact the process of self-organization that delineates how teammates form patterns of coordination (Silva et al., 2013).

The ecological dynamics perspective assumes that various psychological processes (i.e., cognitive, preceptive, active, social, and emotion regulation) form performance behaviors in sport (Araújo, Davids, & Renshaw, in press). According to the authors, it is a misinterpretation to consider that ecological dynamics has a minor part for cognition in human behavior. A fundamental principle in the ecological dynamics approach is the concept of *affordances,* which assumes that humans can perceive the characteristics of the environment as possibilities for actions (Araújo & Bourbousson, 2016). The affordances specify the unique frame of reference for each performer since it is an ecological property that is relative to one’s action capabilities

(Seifert, Komar, Araújo, & Davids, 2016). Using the expert-novice paradigm, there are evident indicators that show the functionality of skilled performers to utilize affordances compared to novices. For instance, the functional behavior of a rock climber is judged by the performer decision-making processes on the climbing wall; while experts consider where to grasp next, they extract environmental cues and climb according to the shape and orientation of the surface holds. However, novices attend to irrelevant cues such as the color and the size of the surface holds, which is less functional to their performance on the climbing wall (Boschker, Bakker, & Michaels, 2002).

In a team context, players extract context-dependent information from the environment to attune their behavior with their teammates, or against other teams (Feigean et al., 2018). In conjunction, players can interact with each other, whether consciously or unconsciously, by implementing collective actions, such as passing the ball or executing an offside trap in soccer (Silva et al., 2013). From this viewpoint, expert teams are grounded in the performers' abilities to share collective affordances during competitive events (Feigean et al., 2018). While the action itself is an illustration of the cognitive process, modeling the multifaceted fabric of performer-environment interactions serves as the appropriate scale of analysis. Thus, the inquiry of sports performance through an ecological dynamics approach pertains to how repeated interactions among athletes result in the emergence of self-organizing patterns of behavior (Araújo et al., in press). The self-organizing coordination tendencies result in *synergies*, that are characterized as "assemblages of components constrained to behave as a single functional unit" (Silva et al., 2016, p. 40). The notion of synergies has emerged in the human movement sciences to describe the synchronization processing of different body parts to achieve a task-specific goal (Araújo et al., in press). Aligned with the natural physical perspective of ecological dynamics, the examination of synergies allows scholars to observe the perceptual attunement to shared affordances between individual performers of sport teams (Silva et al., 2016). When teammates are better able to share affordances under specific-task constraints, they regulate their movements more efficiently, which strengthens the existence of the team synergies. This process is expected to produce higher levels of team coordination, resulting in indicators that are associated with successful team performance (Araújo & Davids, 2016).

Properties of Team Synergies in Sport

Araújo and Davids (2016) conceptualized four components of team synergies in sport: (1) dimensional compression, (2) reciprocal compensation, (3) interpersonal linkages, and (4) degeneracy.

Dimensional Compression. The *dimensional compression* is a process where independent degrees of freedom (DF) of players become coupled, so the synergy has a lower dimensionality since it consists of fewer DF than the set of the consisting ingredients (Araújo & Davids, 2016). When the DF are combined, it enables the DF to regulate each other actions and reduces the dependency of each DF separately (see Figure 1; Riley, Richardson, Shockley, & Ramenzoni, 2011). In sport, environmental and task constraints direct individuals to coordinate their actions in space and time to maintain team cohesion to achieve performance goals (Silva et al., 2016). In this synergy dynamics, the team (high-dimensional system) can be described by *order parameters* that can quantify various spatiotemporal patterns (low-dimensional behaviors). For example, synergistic relations of two professional soccer teams were assessed via a cluster amplitude measure; the investigation that occurred during live matches showed superior mean values for the structure of synchrony in the longitudinal (goal-to-goal) direction rather than the lateral (side-to-side) direction in attacking and defending movements (Duarte et al., 2013).

Furthermore, both teams display better synchronization tendencies over time. Overall, utilizing tools that assimilate synergetic behaviors of sport teams may monitor the perceived affordances and intentions among players (Silva et al., 2016).

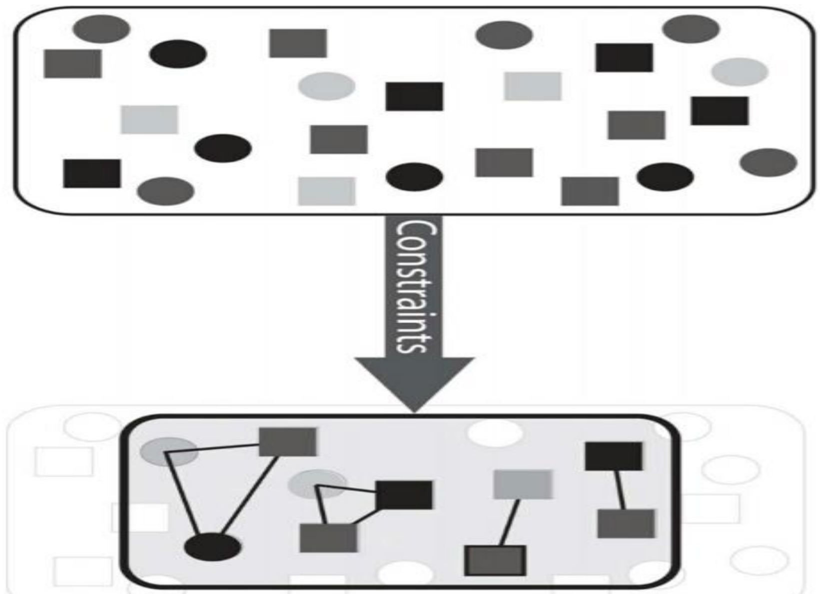

Figure 1.1. An expression of the dimensional compression process; the upper square represents a high dimensional system since each DF operates unconnectedly with the other DF in the workspace. The various task and environmental constraints accelerate the emergence of 'team synergy,' which consequently, facilitates the coordinating behaviors among the DF. The bottom square reflects a lower dimensional system that functions more efficiently and can be measured via team-based variables, that absorb self-organizing behaviors of sport teams (Reproduced from Riley et al., 2011, p. 2; reprinted with permission).

Reciprocal compensation. The second component of team synergies in sport is *reciprocal compensation,* which refers to the ability of the elements in the synergy to execute compensation tendencies where other elements deviate from their expected roles (Araújo & Davids, 2016). While individuals perceive affordances for processes that are associated with the destabilization of the synchrony, they operate compensative behaviors to maintain the task performance goals. For example, during a fast break attack in soccer, the movements of the attackers may leave uncovered field areas that can be compensated by other teammates that readjust their movement direction to these gaps. Correspondingly, a recent study found that 15 weeks of practice led to improved reciprocal compensations of soccer teams that were displayed via decreased delays to required adjustment movements (Silva et al., 2016). The players were faster to find performance solutions that are functional to the homeostasis of the synergy.

Interpersonal linkages. The third ingredient of team synergies in sport is *interpersonal linkages*, which epitomizes by the sharing patterns or the division of labor in the team (Araújo & Davids, 2016). Following the concept of TMM, a team is bounded by the unique characteristics of each individual to obtain specific tasks (Filho & Tenenbaum, in press). Analogs to the Gestalt psychological perspective, the whole is more the sum of its parts, Ingold (2015) argued that a team cannot be described as an “aggregate of discrete individuals,” but rather as a “correspondence.” Therefore, the simultaneous actions among the organisms emerge in mutual shaping, which can be embodied in the coordinating patterns of the team. The use of visual algorithm methods to study collective patterns in different sports has been skyrocketing in the last decade (Araújo & Davids, 2016). Notational data, such as convex hulls (Moura et al., 2013), dominate region methods (Duarte, Araújo, Correia, & Davids, 2012), and heat maps (Pileggi, Stolper, Boyle, & Stasko, 2012) portray the contribution of each player to the emergence of team coordination. While the ecological dynamics approach is a viable framework for studying the conditions that underlie team coordination, notational analysis methods omit the theoretical rationale of performance behaviors (Vilar et al., 2012). However, concepts of the ecological dynamics approach may bridge this gap by emphasizing the conditions which teammates are more likely to display efficient coordinating patterns (Araújo & Bourbousson, 2016). Therefore, this framework can operationalize the fundamental principles for achieving successful and unsuccessful performance in team sports (Vilar et al., 2012).

Degeneracy. The fourth property of team synergies in sport pertains to *degeneracy*. Degeneracy is derived from disciplines, such as neurobiology, neuroanatomy, and genetics, to delineate "complex systems in which structurally different components of the system interact to provide distinct ways to achieve the same performance outcome" (Passos, Araújo, & Davids, 2013, p. 3). Degeneracy, which is unrelated to the concept of degeneration, develops through the emergence of continuous interactions in naturalistic settings (Seifert et al., 2016). These self-organizing behaviors show consistency over time and signify a relatively stable pattern of shared affordances, which can be flexible when needed (Araújo & Davids, 2016). In this sense, flexibility does not contradict the concept of stability. Functioning synergy is more resistant to perturbations, and therefore, can execute adaptable behaviors more efficiently according to changes in the performance environment and the task demands (Seifert et al., 2016). Since skilled teams are more attuned to maintain shared affordances, they are more likely to deploy the platform of degeneracy, which in turn, facilitates the achievement of quality performance outcomes. Previous studies (Araújo & Davids, 2016; Pina, Paulo, & Araújo, 2017) claimed that team ball games contain continuous adaptive interactions, that are seen as degenerate behaviors, and can be absorbed by the diagnostic method of *Social Network Analysis* (SNA). Notably, this framework provides valuable tools to analyze properties that are epitomized by the synergistic nature of degeneracy, such as an objective quantification of the productivity of a network and the relations within a complex structure (Pina et al., 2017).

Social Network Analysis

Living systems consist of relational units that involve dynamic processes to function in the real world. Gene co-expression, animals' community, and peers in the workplace are examples of small-world networks where the relationships between the entities create a social network (Batool & Niazi, 2014). The sociometry method has emerged in the 1930s to analyze social maps with the emphasis of capturing the graphical representations of individuals and their linkages to each other. However, sociometry- the precursor of SNA, was found to serve as a limited tool in quantification and modulization of complex social processes (Lusher, Robins, & Kremer, 2010). SNA, which is based on algorithms and advanced procedures to create social maps, has become the prominent approach to examining interactions among social units (Batool & Niazi, 2014). The distinction of SNA from other existing instruments is embodied by simultaneous macro-and-micro analysis of social systems (Warner et al., 2012). The macro level perspective enables an analysis of the social structure and the possibility to execute a comparison among networks (Clemente, Martins, & Mendes 2016). On the micro-level, scholars utilize empirical tools to measure the relations within the team with consideration of individual attributes (Warner et al., 2012). Taken together, SNA has the potential to augment the scientific investigation of teams in dynamic and complex environments, and consequently, has been used extensively in different contexts, such as sociology, mathematics, health, political science, and business (Rienties, & Héliot, 2018).

Network metrics. The basic principle of SNA corresponds with the synchronization processing of team synergy and assumes the interdependency of entities rather than the mere existence of independent units (Araújo & Davids, 2016). Specifically, organisms in a social map are symbolized as nodes, and the relations between the nodes are signified as ties (Clemente et al., 2016). The input knowledge of these ties is seen as channels which, whether tangible or intangible, resources may flow or be transferred through (Warner et al., 2012). In the context of teams, SNA methods can facilitate the discovery of unobserved collective patterns, such as the diffusion of the information within the team, preferable or neglected links among teammates, recognition of the focal players, and monitoring early signs of coordination breakdowns (Gonçalves et al., 2017; Bourbousson et al., 2015).

Utilizing the network metrics of density and centrality allows researchers to identify and quantify the self-organizing properties of teams. Precisely, the predictor variable of *density* measures the level of connectivity of team members in a particular network (Mclean et al., 2019). When comparing the functionality of a certain structure, high-density networks are characterized by a greater diffusion of information within the team compared to low-density networks, which increases the likelihood of these system to attain their performance goals (Grund, 2012). As some players are more involved than the other teammates, it represents a *centralized* system (Gonçalves et al., 2017). In contrast, in a decentralized network, there is an equal interaction among the players. As it pertains to the later example, the tendency for a homogeneous type of interaction in decentralized networks facilitates the execution of complex tasks since more nodes are likely to take part in the collective efforts of the team (Sueur, Deneubourg, & Petit, 2012).

SNA in sport psychology. While SNA has been ingrained a useful technique in other disciplines, this approach has been hardly approached in the sport research (Lusher et al., 2010). However, the underlying SNA assumption of interdependency is ideally suited to the nature of sport teams. Inevitably, sport teams operate under high-pressure, dynamic, and complex conditions where the emergence of codependent structures is vital to their existence (Cannon-Bowers & Salas, 1990). Wherefore, the codependency relations among the players set the ground for the creation of a network. Furthermore, the conceptualization of SNA acknowledges the team as a unit of study with the appearance of dynamic-complex processes (Warner et al., 2012).

Correspondingly, the investigation of sport teams under the framework of SNA is epitomized by dynamic properties such as cohesion (Anderson & Warner, 2017), leadership (Fransen et al., 2015), and communication (Mclean et al., 2019).

The collecting data of SNA in sports teams are based merely on an n*n table of the roster, where n is the number of team members (Lusher et al., 2010). While most of the SNA surveys are based on a limited nomination procedure on one item (e.g., do you consider X as a leader?), multiple criteria can be combined to utilize different dimensions of the team (Anderson & Warner, 2017). Furthermore, participants can provide responses based on an open-ended list (e.g., who are the leaders of the team?). The rows represent the participants' responses, while the columns reflect the incoming ties to team members (Lusher et al., 2010). Further, this information is formatted as square adjacency matrices (see Figure 2). Most of the breakthroughs in this framework have occurred in the recent years, due to the emergence of innovative SNA software (e.g., Gephi, UCINET, and INSNA); these technologies can extract advanced team properties that had been challenging to be captured beforehand (Lusher et al., 2010).

	1	2	3	4	5
1	–	1	0	1	0
2	0	–	0	1	0
3	0	1	–	0	0
4	0	1	1	–	0
5	0	0	1	0	–

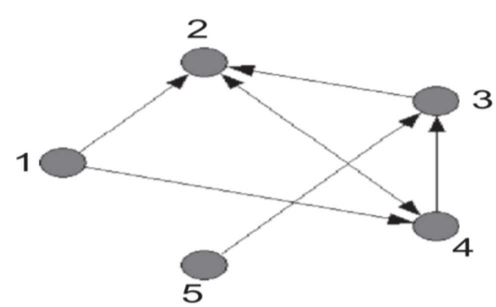

Figure 1.2. An example of the data collection process of SNA. The left side represents the n*n table of the roster, while the right side exemplifies the square adjacency matrices of a seeking advice network; (Reproduced from Lusher et al., 2010, p. 216; reprinted with permission).

SNA and cohesion. Under the notion that a network's behavior in a group is heavily determined by the type of the relationships within the group, meaningful data can be detected by utilizing SNA methods to assess team cohesion in sport psychology (Wise, 2014). Specifically, the variable factor of density fits the construct of cohesion due to the assessment of its internal ties in correspondence to the proportion of the whole networks (Anderson & Warner, 2017). Presumably, a higher ratio of density reflects strong cooperation among players (Clemente et al., 2016). As SNA is based on the explicitly defined relationship among individuals in the team, the Group Environment Questionnaire (GEQ), which is recognized as the dominant measure of team cohesion in sport, assesses general perceptions of cohesion in the team (Warner et al., 2012). A longitudinal study utilized these two methods when measuring social cohesion constructs, such as friendship and efficacy in sport teams (Anderson & Warner, 2017). However, the GEQ and SNA showed contradictory patterns; while the GEQ total scores were significantly decreased throughout the season, the density index of SNA showed an increment of social cohesion constructs. Additionally, the authors assessed the correlation between GEQ and SNA with regards to team performance. While the GEQ scores maintained a positive relationship with team performance, the SNA friendship network had a negative relationship with the overall team performance. Previous SNA studies endorsed this pattern by showing that high performing teams tend to demonstrate low levels of social cohesion in terms of seeking advice and friendship (Warner et al., 2012). Moreover, throughout the quantification of SNA density variable, Wise (2014) challenged the positive relationship between social cohesion and performance. The author claimed to view the connection between social cohesion and performance as an inversely curvilinear relationship. That is, there is an optimal level where social cohesion and performance are maximized. However, insufficient or excessive levels of social cohesion can drive team psychological mechanisms that undermine team performance. Further exploration of social cohesion in sport teams must carefully consider the integration of GEQ and SNA methods and their link to performance, to provide appropriate clarification of the essence of social cohesion in sport psychology.

SNA and leadership. One of the most crucial determinants of team effectiveness in sport is the quality of the leadership in the team. In the past, the conventional approach for capturing leadership emphasized the vertical team dynamics, where there is one leader who is positioned hierarchy above the team (Fransen et al., 2017). Therefore, most of the methodological tools have typically relied on individual-level measures to analyze the leadership quality in sport teams (Fransen et al., 2015). However, in the last decade, the viewpoint has been shifted from the vertical leadership approach towards the notion of shared leadership, which asserts distribution of leadership responsibilities in the team rather than leadership style that only emanates by a prescribed leader (Fransen et al., 2017). When comparing to vertical leadership, the shared leadership is associated with higher team confidence, greater team resilience, a higher task-involving and a lower-involving climate, and a superior team ranking. SNA was found as a proper method to represent the concept of distributed leadership since this technique investigates individual preferences with the integration of social structure (Warner et al., 2012). Notably, the variable factor of centrality recognizes that central nodes to be perceived as the influencing figures within the team structure. This is, SNA may explore team operations beyond the perspective of formal relations (Lusher et al., 2010). A study which analyzed the distribution among formal and informal leaders in 25 sport teams has classified four types of leaders (Fransen et al., 2014); two on-field leadership roles (*task and motivational leader*) and two off-field leadership roles (*social and external leader*). On the field, the *task leader* is the one to charge tactical decision-making processes (an example of such leadership network is presented in Figure 3), while the *motivational leader* instils the emotions that encourage the team members to achieve optimal performance. Off-field, the *social leader* is the one to steer social cohesion processes in the team, while the *external leader* is in charge of club management needs such as relations with media, sponsors, and other external duties. A recent study (Loughead et al., 2016) showed positive correlations among the four types of shared leadership networks to task and social cohesion networks. Specifically, the motivational leadership network was the strongest predictor of task cohesion network, and the social leadership network has emerged as the strongest predictor of the social cohesion network.

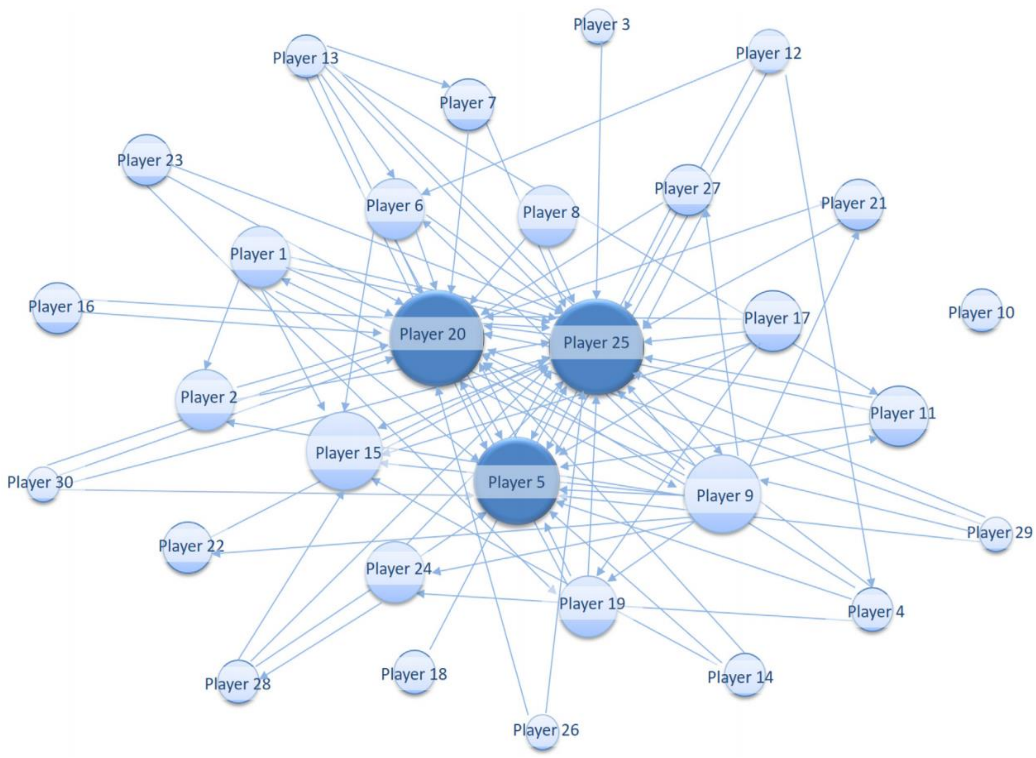

Figure 1.3. A graphical representation of the task-leadership network of an elite Australian football team. The most substantial ties towards players 5, 20, and 25 indicate their perceived role as the task leaders of the team as expressed by the other team members; (Reproduced from Fransen et al., 2017, p. 802; reprinted with permission).

SNA and communication. Sport teams display multidimensional team processes, which in turn, may influence the overall performance. As mentioned earlier in this paper, communication is a primary component that occurs during the actual performance stage (Eccles & Tenenbaum, 2004). The repeated interactions among the teammates are likely to facilitate the establishment of team cognition, which consecutively, impacts communication dynamics within the team and vice-versa (Filho & Tenenbaum, in press). Recent research utilized density and centrality measures to analyze the intra-team communication of one soccer team over 22 games during one season (Mclean et al., 2019). Following every match, the players completed an SNA matrix based on their tactical positions. The players were asked to mention the frequency of on-field communication with each team member and to rate the effectiveness of the communication on their performance. Inclusively, won matches were associated with more involvement of nodes in the overall team communication, which manifests a decentralized network pattern. Furthermore, the increased density score of the team signifies adaptive information exchange in the sake of achieving team goals. While this study consisted of the outcomes of only one specific soccer team, investigating actual relations during live matches intertwines the emotions and the pressures that exist in the competitive sport environment. Ultimately, the literature of sport and exercise psychology can benefit from actual competitive performance studies that describe teams' interactive behavior as a whole rather than using a reductionist analysis of individuals within teams.

Game-Based Interaction Networks

The transformation of independent organisms into synergetic relations stems from the need to face dynamic constraints during complex tasks (Silva et al., 2016). A growing body of research has begun lately to monitor these coordinating behaviors during actual games and links them to performance outcomes (Gonçalves et al., 2017). SNA approach describes the functioning of adaptive systems as a whole and provides a micro-level outlook of the relations within the team and their consequences for the team performance (Clemente et al., 2016). Most of the SNA studies in sport have focused on social cohesion constructs (i.e., friendship and advice-seeking networks) rather than investigating team production processes that are more closely to reflect the concept of task-cohesion (Grund, 2012). Based on the principles of SNA approach, the Game-Based Interaction Networks (GBIN) method can bridge this gap since it is used to assess objective team properties during live matches (Wäsche, Dickson, Woll, & Brandes, 2017). Specifically, this method is functioned for exploring performance results by investigating the ties (e.g., passes) among teammates during sports events. Indeed, each soccer match consists of an average of 1,700 actions, and the passes are considered as the most common performed action, in as much as it constitutes more than 70% of the total operations. Various team metrics can describe these collective behaviors and extract an output that portrays teams' coordination patterns. This data is visualized and provides a useful 'snapshot' information for the coaching staff in real time (Gonçalves et al., 2017).

The application of GBIN studies had been mainly conducted in open skill sports, such as soccer (Gonçalves et al., 2017), basketball (Fewell et al., 2012), and water-polo (Passos et al., 2011), in which the repeated interactions through passing lay the ground for the creation of a structure. The performance in open task environments is imposed by rapid and constant adaptations, where the planning is constrained, and the importance of sharing affordances among the entities is consequential for the synergy functioning (Eccles, 2010). The popular game of soccer serves as a suitable context for analyzing the connection between the structured networks and the overall team performance due to the defined interactions among players, and the existence of objective measurements, such as scoring goals and outcome (Grund, 2012). When inquiring soccer networks, the players are represented by circles, where the direction of the passes indicates interaction among the players (Gonçalves et al., 2017). The higher rate of successful passes among teammates is represented by thicker lines, while thinner or even an absence of lines represents low connectivity among players (see Figure 4). Additionally, when analyzing these collective behaviors, one must take into consideration that players with adjacent tactical positions are more likely to be yoked together (Gonçalves et al., 2017). Inclusively, GBIN provides essential insights based on information from various network metrics, which coaches can utilize for designing practice learning environments and even to make decisions during matches (Clemente et al., 2016).

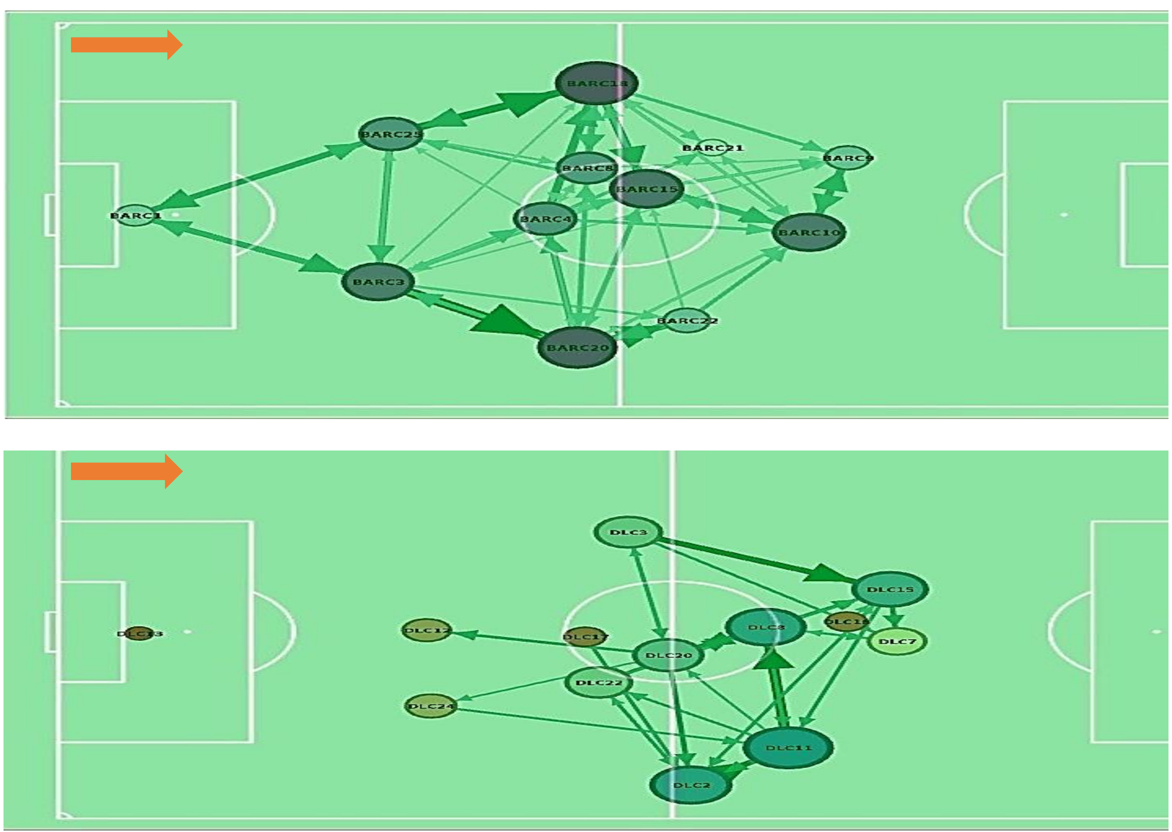

Figure 1.4. (**a**) and (**b**) displays different trends for each soccer team. The circles represent

Figure 4 continued

players involved in the attack, which bigger sizes signify a higher involvement of players. The green arrows indicate the pass direction. The origin of the arrow represents the player who passes the ball, and the arrowhead represents the player who received the ball. Thicker lines illustrate more passes occurring between specific players (e.g., the connection between player 18 and 25 at image a, and the one-direction link between player 11 to 8 at image b) and thinner lines signify fewer passes taking place among players (e.g., the lack of interaction between player 3 and 17 at image b; Reproduced from Blatt, 2019, p. 46; reprinted with permission).

GBIN Metrics

Densities. The predictor variable of *network density* determines the level of connectivity among players (Mclean et al., 2019). Based on a dataset of 760 English Premier League soccer matches, Grund (2012) found that greater values of network density were associated with better performance. As noted, a higher ratio of density indicates a tendency to play as a whole rather than a condition where all the players are isolated (Clemente et al., 2016). Comprehensively, teams with interrelated passing patterns are more likely to show fewer coordination breakdowns when building their attacks, which consequently, are considered as functional behavior.

An additional variable factor that serves for analyzing density dimensions in GBIN is the *clustering coefficient*, which measures the degree to which entities in a network tend to cluster together (Clemente et al., 2016). While network density is based on calculating the percentage of all possible two-path ways, the clustering coefficient is derived by computing the percentage of all possible triangles in the network. Previous evidence suggests that average clustering coefficient scores discriminated among teams of different levels; the best national soccer teams in FIFA World cups 2010 and 2014 maintained high values of clustering coefficient throughout these tournaments compared with less successful teams (Clemente et al., 2015).

Centralities. The variable of *centrality* consists of micro-and-macro advantages when analyzing social structures. In general, centrality is calculated to assess the quality of interactions of a network (Gonçalves et al., 2017). The closer the centrality score to 1, the more likely the network has a star-like topology, signifying a high-dependence on a specific player (Clemente et al., 2016). In this matter, previous GBIN studies found that the team's strong dependence on specific players affects the overall performance negatively (Gonçalves et al., 2017). Vice versa, when the centrality index closes to 0; the more likely the nodes of the network have on average the same connectivity (Clemente et al., 2016). Teams with a tendency toward equal type of interactions amongst their players are characterized as a *decentralized network,* which ultimately provides more flexibility to express the mutual affordances in multiple ways (Carely, 1997). In this sense, decentralized teams were found to have 8% higher chances of scoring than centralized teams (Grund, 2012). Furthermore, scholars can utilize centrality properties to identify the most influential players within a team (Clemente et al., 2016). This micro analysis procedure allows direct assessment of the contribution of each player in the network. Given the depth of this component, most commonly GBIN centrality measures include weighted In-degree centrality, weighted out-degree centrality, betweenness centrality, and closeness centrality.

The nature at which information is received and produced, characterizes the real-world networks. The *weighed In-degree centrality* parameter contemplates the network's distribution, as the players are receiving the ball. On the other hand, the *weighed Out-degree centrality* evaluates the distribution of the network when players are delivering the ball (Grund, 2012). Recent GBIN study that examined the parameter of the in-degree centrality defined it as the "prominence level of each player to be the target of his teammates to pass the ball. (Clemente et al., 2015, p. 214)." While computing the in-degree centrality on the network level, high values signify that only one or a few players are showing the affordances for receiving the ball; vice versa, low values of in-degree centrality indicate a passing strategy which the majority of the team involves in receiving the ball in the match (Mclean et al., 2019). Correspondingly, the out-degree centrality considers the importance of each player to operate delivery of passes (Clemente et al., 2015). A soccer network that is characterized by high values of out-degree centrality bases the delivery of passes on one or few players, while a low score of out-degree centrality reflects that most of the team players were involved in the establishment of the passes' strategy (Mclean et al., 2019).

An integrative view of the centrality variable suggests that when teams are less dependent on specific players, they maintain a balanced passing strategy. *Betweenness centrality* measures how the fluidity of interaction is dependent on particular nodes (Gonçalves et al., 2017). This property assumes that the essential node is the one which is connecting different parts of a network, acting as a bridge between one cluster of nodes and another (Newman, 2005). This node holds a certain level of power by frequently allowing to choose the direction of information within a network (Freeman, 1978). In soccer, these players influence the ball fluidity when the team possesses the ball. Lower betweenness centrality score of a system indicates that more players are likely to engage in this role to facilitate the ball-flow of the network. Consequently, these teams are characterized by expeditious passing patterns that are associated with superior performance (Gonçalves et al., 2017).

Closeness centrality quantifies the proximity between a player to his teammates. Specifically, the nodes with the highest closeness centrality can reach other nodes more easily (peña & Touchette, 2012). In soccer, high values of closeness centrality signify a player who can reach more players with fewer passes. These players are most likely represented by a midfielder because they are commonly in close connection with both the defensive and offensive lines, in addition to the left- and right-wing players (Gonçalves et al., 2017). Overall, this variable factor indicates an efficient behavior for spreading information in the network. In the recent years, various algorithms have been developed to assess closeness centrality score of complex networks, where higher values of closeness centrality assume a positive meaning in the node proximity of the network (Batool & Niazi, 2014). As opposed to other centrality parameters which the network efficiency was associated with low centrality indices, networks with a higher rating of closeness centrality were associated with better performance in soccer games (peña & Touchette, 2012; Gonçalves et al., 2017). A summary of all GBIN indicators is presented in Table 1.

Table 1

Summary of GBIN indicators, value ranges, interpretations, and links to performance

GBIN Indicator	Value range	Interpretation	Link to Performance
Network density	0-1	Signifying the level of connectedness among teammates	High-density networks reflect strong cooperation among players. Associated with superior performance in the English Premier League and international tournaments
Clustering coefficient	0-1	Denoting the degree of clustering among teammates; based on the percentage of all possible triangles in the network	High values of clustering coefficient were maintained among the best national teams in FIFA World cups 2010 and 2014 compared with less successful teams
Weighed In-degree centrality	0-1	Assessing the network's distribution, as the players are receiving the ball	Low values of in-degree centrality indicate a passing strategy which the majority of the teammates show affordances for receiving incoming passes in the match
Weighed Out-degree centrality	0-1	Evaluating the network's distribution, when players are delivering the ball	Low score of out-degree centrality reflects that most of the teammates were involved in the establishment of the passes' strategy
Betweenness centrality	0-1	Quantifying the occurrence that a node connects between one cluster of nodes and another	Low values of betweenness centrality reflect efficient fluidity of the ball with less dependency on specific players
Closeness centrality	0-1	Computing the extent of proximity between players; how easy it is for teammates to reach each other	High rating of closeness centrality indicates an efficient behavior of the network, where players can collaborate more easily with each other

Complementary Information. Besides the GNIB metrics, additional factors that increase the odds of winning at a soccer match must be presented alongside with the outcome to fully capture the layers of a soccer match (Collet, 2013). A probabilistic model suggests that the classic parameter of the number of shots from the box (i.e., the 18-yard box next to the opponent's goal) can be misleading since there are differences in the quality of the shots in this area (Fairchild, Pelechrinis, & Kokkodis, 2018). To overcome these shortcomings, the *expected goals* (xG) factor estimates the likelihood of a goal attempt resulting in a goal. An integration quotient of the location, distance, shot speed, and shot angle is linked to the probability to score a goal (Rathke, 2017). Inclusively, soccer teams that are characterized by better shot effectiveness are more likely to win. The Danish club of FC Midtjylland provided a practical example of the prediction of team performance by the xG factor. Having recruited its players using this factor and maintaining the highest xG scores throughout the season league resulted in winning the first Danish league title of the club in 2015.

The total number of passes has been increased by 40% in the last four decades, and this factor remains a strong predictor for success in soccer (Bush et al., 2015). The coefficient of *overall number of accurate passes*, which counts all the accurate team passes in a game, was found to discriminate between successful and unsuccessful teams (Evangelos et al., 2014). Specifically, an analysis of passing patterns in European leagues showed that on average, winning teams performed around 150 passes more than the losing teams. *Passes accuracy* is another factor that has the potential to display differences between successful and unsuccessful teams (Collet, 2013). This factor represents the fraction of precise passing (completed passes/ total passes) of a team during a soccer match. In addition to reaching a higher rating of passes accuracy, winning teams were also found to reduce the passes accuracy of their opponents (Evangelos et al., 2014). At a practical level, the indicator of passes accuracy increases the speed and the quality of the offensive efforts, which consequently, has an impact on the team performance.

Limitations and Future Directions of GBIN Studies

While GBIN represents a powerful analytic approach in sport settings, one must be aware of the potential limitations of this method. Concerning sampling problems, most GBIN studies are hinged on a small sample of teams; typically, the majority of the GBIN samples are based on one-to-three sports teams (e.g., Passos et al., 2011; Clemente et al., 2015; Gonçalves et al., 2017). Likewise, most of these studies consisted of less than 12 matches overall (e.g., pina et al., 2017; Cotta et al., 2013). Moreover, Previous soccer teams that deployed network approach to compare teams have relied on tournaments that occurred during a time frame of two-to-three weeks and were played for three to seven games per each team (e.g., Pena & Tochette, 2012; Clemente et al., 2015). While GBIN provides valuable information in terms of capturing the evolution of team coordination processes, the absence of longitudinal studies violates the measurement of these changes (Fransen et al., 2015). Thus, the inclusion of big samples (e.g., grund, 2012) that combine a diversity of teams and matches over a prolonged time such a season league can maximize the validation of GBIN approach.

A common misconception in this regard occurred due to the arbitrary classification into successful or unsuccessful teams. When using the expert-novice paradigm, there is relatively consist consensus on the background variables that differentiate between the expert and the novice athletes, such as, experience, knowledge about the task, and a variety of strategic behavioral aspects (Thomas & Thomas, 1994). However, classifying professional soccer teams under the definition of novice teams may disproportionate the theoretical distinction between expert and novice teams. To standardize the taxonomy of the operational definitions of expertise in sport, a recent study proposed a classification system based on adequate criteria (Swann, Moran, & Piggott, 2015). Following a thematic analysis of 91 expertise studies in the literature of sport and exercise psychology, the authors recognized four types of expert stages along a continuum of competitiveness. The lower level of expertise refers to *Semi-elite athlete/team*, which considers participants that are underneath the top standard of performance in their sport, such as athletes in talent development programs and ball teams playing in the 2nd to 4th tier-leagues. Next, the taxonomy of *competitive elite athlete/team* comprises performers who compete at the top level in their sport, with the absence of any success in that specific domain, such as athlete's participation in international competitions and competitive teams in top tier leagues. The definition of *Successful-elite athlete/team* recognizes a level of expertise which is associated with sustained participation in the highest standard of performance accompanied by an occasional success at that level, such as winning a medal in an international event and team's participation in a major international tournament. The characterization for the high-profile achievers in sport is epitomized by *world-class elite athlete/ team*, which illustrates performers with a constant success at the highest level of performance over protracted periods, such as recurrent winning of medals in major international events and team's sustained success at the top international level. Altogether, when defining the samples of GBIN studies, future studies must be guided by reliable taxonomy standards for judging the level of expertise.

When it comes to collecting data, the first limitation concerns the reliance on a single item for assessing sport teams' networks. To minimize the probability of skewed results, future studies must include a full model which meets the criteria of a good fit among different networks that assess the same core concept (Young, 2011). Moreover, missing information can be a significant problem since GBIN relies on interdependency relations among the individuals in the team (Lusher et al., 2010). Previous studies proposed different criteria to handle the problem of missing data; it seems that there is a consensus around having 70% of the dataset (pryke, 2017). Third, adopting a binary approach to collect data focuses on a narrow scope of options (i.e., yes-no questions), which neglected the opportunity to explore the strength of the ties within the team (Grund, 2012). Conducting studies that assess the strength of the ties is more informative in terms of capturing team coordination properties (Warner et al., 2012).

With reference to conceptual limitations, the emergence of self-organizing behaviors can be manifested in different ways. The paramount goal of ecologies is to understand how organisms operate in different live social contexts (Araújo & Davids, 2016). However, current performance analyses approaches neglect essential contextual information which pertains to the performance conditions that afford the emergence of specific successful actions. For example, some of the studies were conducted in a practice environment that contradicts the nature of ecological dynamics (Vilar et al., 2012). That is, future GBIN studies must incorporate various environmental considerations, such as live matches from various leagues and different expertise stages, to improve the application of the proposed framework on competitive performances. In this sense, when sport psychology scholars and practitioners utilize GBIN methods to their needs, they must approach it cautiously to gain the benefits of this technique.

Hypotheses

The GBIN method serves as an alternative line of research to measure team coordination in live matches in different dynamic sports (Wäsche et al., 2017). While only a few studies were conducted using this method in the domain of soccer, these studies are overlooking important contextual variables, such as a comparison between and within teams in a different level of expertise during a time frame of a season league (Gonçalves et al., 2017). Therefore, conducting research which examines the consistency of coordination patterns and its constructs between and within teams in different levels, may evolve new disclosures regardless of the shared affordances among teammates and its relation to performance. Given the variety of indices in the study, this approach can endorse an initial set of benchmarks to distinguish between the successful or unsuccessful network structuring of sports teams (Bourbousson et al., 2015). Additionally, visual network graphs may facilitate visual inspection of the teammates' coordination patterns. Jointly, this view has the potential to lay the foundations for investigating the GBIN method as an operational definition of team coordination in the sport. Given that previous studies using this method showed that high density (Grund, 2012), low centralization (Gonçalves et al., 2017), and higher passes indices (Collet, 2013) are associated with higher probabilities for superior performance, it is hypothesized that:

(H1) World-class elite teams will present coordinative patterns of higher density ratings (network density and average clustering coefficient), lower centrality ratings (betweenness, weighted in-degree, weighted out-degree centrality, and high closeness centrality), higher passes indices (overall number of accurate passes, and passes accuracy percentage) and better performance (expected and actual goals) compared to the competitive-elite teams.

(H2) When world-class elite teams play against each other, they will present similar coordinative patterns of density ratings (network density and average clustering coefficient), centrality ratings (betweenness, weighted in-degree, weighted out-degree centrality, and closeness centrality), passes indices (overall number of accurate passes, and passes accuracy) and performance (expected and actual goals).

(H3) The competitive-elite teams will present relatively similar patterns of density ratings (network density and average clustering coefficient), centrality ratings (betweenness, weighted in-degree, weighted out-degree centrality, and closeness centrality), passes indices (overall number of accurate passes and passes accuracy percentage) and performance (expected and actual goals).

CHAPTER TWO

METHOD

Sampling

A priori statistical power analysis for a MANOVA with two levels and eleven dependent variables was conducted using G*Power (Faul, Erdfelder, Buchner, & Lang, 2009) to determine a sufficient sample size using an alpha of 0.05, power of 0.80, and a large effect size (f = 0.88), determined from the preliminary study of "Team Mental Models and Game-Based Interaction Networks in Soccer (n = 30; Blatt, 2019)." Based on the above-mentioned assumptions, the desired sample size for the first hypothesis is 32. Thus, the proposed sample size of 36 matches is more than adequate for testing the first hypothesis. Further, 30 matches were sampled to test the second hypothesis. The third hypothesis consists of 36 matches of the competitive-elite teams.

Professional soccer team is considered the unit of analysis in this study. This study samples 66 matches from the La-Liga Spanish soccer league, English Premier League, and German Bundesliga, which hold a reputation as the top soccer leagues in Europe, according to official ranking of UEFA (Union of European Football Associations). The criteria used to determine the status of these leagues consider the results of the teams who represent the country in international tournaments over the last five seasons, with attributions to every specific season (for more details, see Union of European Football Associations, 2019). In conjunction to the postulation that there are relatively more objective criteria to determine expertise in sport compared to other domains (Swann et al., 2015), the UFFA club criteria are utilized to validate the level of expertise of the competing club teams in the study. Similarly, the UEFA club coefficients are calculated by considering the club results in international tournaments over the past five seasons, with a weighting of 20% of the country coefficient rankings at that time. Aligned with the suggested taxonomy of expertise by Swann and colleagues (2015), the teams which reached the top two standings in each league, considering the standings at the end of season 2018/2019, match the requirements for being regarded as world-class elite teams. Herein, the club teams of Atlético Madrid (the 4th best team in Europe, 127.000 points), FC Barcelona (the 2nd best team in Europe, 138.000 points), Manchester City FC (the 6th best team in Europe, 106.000 points), Liverpool FC (the 11th best team in Europe, 91.000 points), FC Bayern München (the 3rd best team in Europe, 128.000 points), and Borussia Dortmund (the 13th best team in Europe, 85.000 points) evidently attain the benchmark of the highest standard of performance. The teams which reached the third and fourth standings in the league hold the reputation of world-class elite teams since they appear in the top 40 soccer club in Europe based on the UEFA club coefficients rating (e.g., Real Madrid CF, the 1st best team in Europe, 146.000 points, 3rd place in the La-Liga Spanish soccer league; Tottenham Hotspur, the 17th best team in Europe, 78.000 points, 4th place in the English Premier League). To examine differences between the world-class elite teams amd teams at a relatively lower level of expertise, the study sampled the three teams which relegated to the 2nd tier leagues in the La-Liga Spanish soccer league, English Premier League, and German Bundesliga, respectively. These nine soccer teams have not competed in the international stage, as evidenced by disqualifying from being included in the total best 421 standings of the UEFA club coefficients. While these teams compete at the top leagues, without objective achievements at that specific stage, it is appropriate to classify the relegated teams under the expertise taxonomy of competitive-elite teams (Swann et al., 2015).

The study is deliberately focused on games of six world-class elite teams which reached the top two standings in each league, considering the standings at the end of season 2018/2019.

A total of 72 matches of FC Barcelona (12 games), Atlético Madrid (12 games), Manchester City FC (12 games), Liverpool FC (12 games), FC Bayern München (12 games), and Borussia Dortmund (12 games) were analyzed. To identify synergetic patterns across games, each of these six teams were analyzed when playing six games against the teams which reached the top four standings in their league at the end of 2018/2019 (i.e., world-class elite teams) and six games against the three teams which relegated to second-tier league at the end of season 2018/2019 (i.e., competitive-elite teams). The games were sampled on a prolonged time of one competitive season (i.e., from August 2018 to May 2019). Since each league comprises two rounds of games, each game is played twice in different locations (i.e., home and away games) and in different time frames (e.g., FC Bayern München played an away game against Borussia Dortmund in November 2018, and FC Bayern München played a home game against Borussia Dortmund in April 2019). Accordingly, the study sampled both games for controlling the contextual factor of the game location.

SNA Measures: Interaction Network Parameters

Density.

(1) **Network Density**

$$S = \frac{L}{N(N-1)}$$

Network density is evaluated as the number of existing lines (L) divided by the number of maximum possible lines, N(N-1). Accordingly, in a hypothetical state where all the players are isolated, the score (S) of this network is 0; In contrast, when all the players are well-connected to each other, the score of the unified system is 1 (Pina, Paulo, & Araújo, 2017; Warner, Bowers, & Dixon, 2012).

(2) **Average Clustering Coefficient**

$$c_i = 2e_i / k_i(k_i - 1)$$

The clustering coefficient (Ci) is calculated as the ratio of the number of triangles formed by a player (i) with its teammates and the maximal number of possible triangles including these players. When Ci = 1 a player and its neighbors are fully interconnected and form a clique; and when Ci = 0 the players and the neighbors are disconnected (Boguñá, Pastor-Satorras, Díaz-Guilera, & Arenas, 2004).

Centrality.

(3) **In-Degree Centrality**

$$C_I = \frac{\sum_{i=1}^{N}(C_{IS}^{*} - C_{IS}(i))}{(N-1)IT}$$

Where C^*_{IS} represents the number of passes of the player who receives most of the passes in the team, while $C_{IS}(i)$ signifies the number of received passes of the other players in the team. The denominator is the sum of all incoming passes within a team. When all players receive the same number of passes, then $CI = 0$. whereby when only one player obtains all the incoming passes, then $CI = 1$ (Grund, 2012).

(4) **Out-Degree Centrality**

$$C_O = \frac{\sum_{i=1}^{N}(C_{OS}^{*} - C_{OS}(i))}{(N-1)IT}$$

The out-degree centrality equation is based on an analogous to the in-degree centrality of a team: $C_O = 0$ when all the players deliver the same number of passes, while $C_O = 1$ means that one player sends all the passes without production of outcoming passes by his or her teammates (Grund, 2012).

(5) **Betweenness Centrality**

$$C_B(i) = \frac{1}{90} \sum_{j \neq k \neq i} \frac{n_{jk}^i}{g_{jk}}$$

Where i represents the node which is acting as the intermediate between the players j and k. Where n^i_{jk} is the number of geodesic paths from j to k going through i and gjk is the total number of geodesic paths between j and k. The normalization factor 1/90 ensures $0 \leq C_{B\,(i)} \leq 1$ (Pena & Tochette, 2012)

(6) **Closeness Centrality**

$$C_C(v) = \sum \frac{1}{dist(v,t)}$$

Calculated as the sum of the shortest path between a certain player (v) and all the other players in the network; for instance, player t. The shorter the paths, the easiest to reach this player in the network (Batool & Nizai, 2014).

Passes

Overall Number of Accurate Passes. Sum of all the accurate team passes in a game (Bush et al., 2015).

Passes Accuracy Percentage. Fraction of precise passing of a team during a soccer match (completed passes/ total passes; Collet, 2013).

Performance Outcomes

Goals Scored. The number of scored goals for a team (Collet, 2013).

Goals Conceded. The number of scored goals against a team (Collet, 2013).

Expected goals (xG). Refers to the likelihood to score a goal from a given situation based on spatial and contextual features. The xG is expressed as a number between 0 and 1, with 1 being a certain goal. An expected goal of 0.25 means that one out of every four occasions results in a goal (Rathke, 2017).

Procedure

The average location of the players, the expected goals (xG) scores, and the passing data for this study was drawn from the Wyscout platform (Wyscout Spa, Italy). The use of match analysis report has grown in the last decade since it consists of the most important features to describe the collective behavior patterns of sport teams (Clemente et al., 2016). The exploratory network analysis was conducted via an open source software (Gephi) that enables the setting and manipulation of SNA components (i.e., nodes and links), calculation of the SNA features (i.e., network density and betweenness centrality), and to generate graphical networks for identification of visual patterns (Bastian, Heymann, & Jacomy, 2009). While all the types of passes are treated similarly, the graphical representation would display ties that signify three passes and more, to improve the user interface when observing the games. Players were included in the analysis if they played for at least 30 minutes in a match. The current research proposal was approved by the institutional review board (IRB) at Florida State University.

Data Analysis

The SNA coefficients (network density, average clustering coefficient, betweenness centrality, weighted in-degree centrality, weighted out-degree centrality, and closeness centrality) were calculated via Gephi software 0.92. SPSS 25.0 was used to analyze the data.

Descriptive statistics are presented, including the means of the dependent variables and the graphic representations of the networks for matches played.

One-way multivariate analysis of variance (MANOVA) statistical tests followed by one-way analysis of variance (ANOVA) tests were performed to examine the first research hypotheses. The independent variable in these analyses was epitomized by the expertise stage of the teams, while the dependent variables were the densities, centralities, passing indices, and performance outcomes. Moreover, stepwise multiple linear regression analyses were performed to test the predictive power of the coefficient factors (i.e., densities and centralities) on each performance parameter (i.e., passes accuracy percentage, goals scored, and expected goals). Dummy variables were coded to differentiate among world-class elite teams who won from those who did not win, and MANOVAs followed by ANOVAs were carried out to test the second research hypothesis. Similarly, dummy variables were coded to differentiate among the competitive-elite teams who won from those who did not win, and MANOVAs followed by ANOVAs were executed to test the third research hypothesis. Collinearity and homoscedasticity assumptions were tested, and transformation adjustments were executed following violations of these assumptions.

CHAPTER THREE

RESULTS

Descriptive Statistics

The descriptive statistics consisting of means and visual representations of teams' networks are presented in Tables 17, 18, and 19 (see Appendix A- descriptive statistics data). Table 17 presents a sample of three matches between world-class elite teams and competitive-elite teams. The comparisons of means and visual representations demonstrate different patterns between the world-class elite teams and the competitive-elite teams. The differences pertain to the coordination and performance indices (i.e., centrality, density, passes, and performance). For instance, the high-density scores (i.e., close to 1), together with the dense visual structures, highlight the higher interdependency of the world-class elite teams compared to the competitive-elite teams.

Table 18 presents a sample of three matches among the world-class-elite teams. Comparisons of means and visual representations indicate minor differences among world-class elite teams with regards to the coordination and performance indices. Table 19 presents means and visual representations of three competitive-elite teams. Comparisons of means and network configurations point out relatively similar patterns concerning the centrality, density, passes, and performance indices. It is seemingly visible that the competitive-elite teams demonstrated centralized structures (i.e., close to 1) and a reliance on a few players in their passing strategy.

Correlations amongst the variables

Pearson correlation coefficients were calculated in the general sample of games amongst and within the dependent and independent variables (see Table 2). The magnitudes of correlations were interpreted as follows (Evans, 1996): 0.00-0.09 trivial; 0.10-0.29 small; 0.30-

0.49 moderate; 0.50-0.69 large; 0.70-0.89 very large; and >0.90 nearly perfect. High correlations were expected to emerge within the four clusters of centrality, density, passes, and performance, and medium to high correlations among the clusters. Notably, robust correlations emerged between network density and average clustering coefficient (r =.89), and between the variable of overall number of passes and passes accuracy percentage (r =.87). For the most part, the coefficients of weighted in-degree centrality and weighted out-degree centrality have not shown significant correlations with the other coefficients in the model. Nonetheless, there were significant correlations in the following matrix among the coefficients of the other centralities (i.e., closeness and betweenness), the densities, the passes, and the performance indices. While moderate-to-high correlations were found among the coefficient of closeness centrality and the SNA factors, this coefficient showed small, trivial, and non-significant correlations with the passes and performance outcomes.

Table 2
Pairwise correlation matrix among variables in the general sample

Variables	2	3	4	5	6	7	8	9	10	11
1.Closeness Centrality	-.62**	-.22*	-.13	.63**	56**	.24**	.19*	.07	-.12	.19*
2.Betweenness Centrality	-	.16	.12	-.58**	-.47**	-.33**	-.29**	-.18*	.20*	-.24**
3.Weighted in-degree Centrality		-	.55**	-.19*	-.14	.01	-.01	.02	.02	-.05
4.Weighted out-degree Centrality			-	-.14	-.04	.13	.12	.07	-.01	.04
5.Network Density				-	.89**	.50**	.42**	.31**	-.37**	.36**
6.Avg. Clustering Coefficient					-	.56**	.48**	.31**	-.42**	.38**
7.Overall number of accurate passes						-	.87**	.53**	-.46**	.53**

Table 2 continued

8.Passes accuracy percentage	-	.51**	-.36**	.50**
9.Goals allowed		-	-.25**	.71**
10.Goals Conceded			-	-.28**
11.Expected Goals				-

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

Coordinative and Performance Comparisons for Team Caliber

The first research hypothesis assumed that world-class elite teams would display higher density ratings, lower centralization ratings, higher passes indices, and superior performance when playing against the competitive-elite teams. To test this hypothesis, means and SDs were calculated for each cluster of centrality, density, passes, and, performance, and a one-way multivariate analysis of variance (MANOVA) followed by a one-way variance of analysis (ANOVA) were conducted accordingly. These analyses were based on the direct games between world-class and competitive-elite teams. Specifically, the analyses were conducted using team caliber (i.e., world-class elite team/ competitive-elite team) as the independent variable, and the four centralities (i.e., closeness centrality, betweenness centrality, weighted in-degree centrality, and weighted out-degree centrality), two densities (i.e., network density and average clustering coefficient), two passing indices (i.e., overall number of passes and accurate passes percentage), and three performance outcomes (i.e., goals allowed, goals conceded, and expected goals) as the dependent variables.

Centrality cluster. For the centrality cluster, Levene's test of variance differences between the teams' caliber were as follows: closeness centrality (p = .12), betweenness centrality

(p = .68), weighted in-degree centrality (p = .21), weighted out-degree centrality (p = .17) – all non-significant. Using the Wilks' Lambda test, the results revealed significant differences between the world-class elite teams and competitive-elite teams for the centrality cluster, Wilks' $\lambda = .810$, F (4, 67) = 3.54, $p < .006$, $\eta 2$= .19. The univariate analysis alongside means and SDs are shown in Table 3.

Table 3
Means, SDs, and univariate ANOVA for centrality cluster by team caliber

	Team Caliber						
	World-Class Elite (n=36)		Competitive-Elite (n=36)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1.Closeness Centrality	.80	.14	.72	.08	8.07**	.10	.71
2. Betweenness Centrality	.03	.01	.04	.01	10.57**	.13	1.00
3. Weighted in-degree centrality	.60	.15	.58	.18	.40	.01	.18
4.Weighted out-degree centrality	.72	.13	.68	.19	.91	.01	.25

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

Subsequent univariate analysis applied to the centrality indices revealed significant differences among world-class elite teams and competitive-elite teams for closeness centrality, F $(1,70) = 8.07$, $p = .006$, $\eta_p^2 = .10$, and betweenness centrality, F $(1,70) = 10.57$, $p = .002$, $\eta_p^2 =$ .13. The higher closeness centrality scores among the world-class elite teams compared to the competitive-elite teams (M =.80, SD = .14 vs M =.72, SD = .08; d = .71), indicate that players of the world-class elite teams displayed greater tendencies to reach each other more easily in the passing networks. In addition, the betweenness centrality index which was found to be smaller among world-class elite teams than in competitive-elite teams (*M* =.03, *SD* = .01 vs *M* = .04, *SD* = .01; *d* = 1.00), reveals a more efficient scattering of passes' strategy among the world-class elite teams. However, there were non-significant differences for team caliber in the other centrality parameters, including weighted in-degree centrality (p = .53), and weighted out-degree centrality (p = .34).

Density cluster. Levene's test of equality of variance indicated nonsignificant variations in the density indices, namely, network density (p = .17) and average clustering coefficient (p = .05). Applying the Wilks' Lambda test, the one-way MANOVA revealed significant differences among the world-class elite teams and competitive-elite teams for the density cluster, Wilks' λ = .574, F (2, 69) = 25.57, p < .001, $\eta 2$= .42. The univariate analysis alongside means and SDs are shown in Table 4.

Table 4
Means, SDs, and univariate ANOVAs for density cluster by team caliber

	Team Caliber						
	World-Class Elite (n=36)		Competitive-Elite (n=36)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Network Density	.77	.12	.60	.15	30.07**	.30	1.25
2. Avg. Clustering Coefficient	.81	.09	.63	.14	45.08**	.39	1.53

** p < .01.
* p < .05.

The univariate analysis yielded a significant difference among the teams in the indices of network density, F (1,70) = 30.07, p = .001, η_p^2 = .30, meaning that the world-class elite teams presented more efficient two-path ways of network clustering than the competitive-elite teams (*M* =.77, *SD* = .12 vs *M* = .60, *SD* = .15; *d* = 1.25). Additionally, the results revealed a significant difference between team caliber for the variable of average clustering coefficient, F (1,70) = 45.08, p = .001, η_p^2 = .39, pointing out that the world-class elite teams clustered more efficiently in three-path ways structuring than the competitive-elite teams (M =.81, SD = .09 vs M = .63, SD = .14; d = 1.53).

Passes cluster. While Levene's test of error variances indicated nonsignificant variations for the variable of overall number of accurate passes (p = .09), it proved statistically significant differences for passes accuracy percentage (Levene's test, F = 5.01, p = .03). Using the Pillai's trace test, the results revealed significant differences among the world-class elite teams and competitive-elite teams for the passes cluster, *Pillai's trace* = .679, F (2, 69) = 73.08, p < .001, $\eta 2$ = .68. The univariate analysis alongside means and SDs are shown in Table 5.

Table 5
Means, SDs, and univariate ANOVAs for passes cluster by team caliber

	Team Caliber						
	World-Class Elite (n=36)		Competitive-Elite (n=36)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Overall number of accurate passes	580	129	257	96	145.83**	.68	2.84
2. Accurate passes percentage	.88	.04	.79	.06	73.50**	.51	1.76

** p < .01.
* p < .05.

For the passes indices, a significant difference emerged between teams in overall number of accurate passes, F (1,70) = 145.83, p = .001, η_p^2 = .68, showing that world-class elite teams produced higher number of accurate passes than the competitive-elite teams (M =580, SD = 129 vs M = 257, SD = 96; d = 2.84). Similarly, the accurate passes percentage was found to be statically significant between the teams, $F\ (1{,}70) = 73.50$, $p = .001$, $\eta_p^2 = .51$, indicating that world-class elite teams obtained more accurate passing percentage in contrast to competitive-elite teams (M =.88, SD = .04 vs M = .79, SD = .06; d = 1.76).

Performance cluster. Levene's test for homogeneity of variances proved statistically significant differences for goals allowed (*Levene's test*, $F = 14.88$, $p = .001$), goals conceded (*Levene's test*, $F = 14.88$, $p = .001$), and expected goals (*Levene's test*, $F = 11.13$, $p = .001$). Utilizing the Pillai's trace test, the results indicated statistically significant differences among the world-class elite teams and competitive-elite teams for the performance cluster, *Pillai's trace* = .662, $F\ (3, 68) = 44.43$, $p < .001$, $\eta 2 = .66$. The univariate analysis alongside means and SDs are shown in Table 6.

Table 6
Means, SDs, and univariate ANOVAs for performance cluster by team caliber

	Team Caliber						
	World-Class Elite (n=36)		Competitive-Elite (n=36)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Goals Allowed	2.86	1.85	.44	.65	54.43**	.44	1.75
2. Goals Conceded	.44	.65	2.86	1.85	54.43**	.44	1.75
3. Expected Goals	2.12	1.16	.76	.49	42.09**	.37	1.53

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

A one-way ANOVA revealed a significant team effect in goals allowed, $F\ (1{,}70) = 54.43$, $p = .001$, $\eta_p^2 = .44$, indicating that the world-class elite teams scored more goals than the competitive elite teams (M =2.86, SD = 1.85 vs M = .44, SD = .65; d = 1.75). Likewise, a significant team caliber effect emerged for goals conceded, $F(1{,}70) = 54.43$, $p = .001$, $\eta_p^2 = .44$, indicating that world-class elite teams allowed less goals than competitive-elite teams (*M* =.44, *SD* = .65 vs *M* = 2.86, *SD* = 1.85; *d* = 1.75). Additionally, the team caliber for expected goals parameter was significant, $F\,(1{,}70) = 42.09$, $p = .001$, $\eta_p^2 = .37$, meaning that the world-class elite teams displayed higher probabilities to score goals over the competitive-elite teams (*M* = 2.12, *SD* = 1.16 vs *M* = .76, *SD* = .49; *d* = 1.53).

Multiple linear regression analyses. Multiple linear regression analyses were carried out to test the first hypothesis. The analyses estimated the predictive power of the coefficient factors (i.e., closeness centrality, betweenness centrality, weighted in-degree centrality, weighted out-degree centrality, network density, and average clustering coefficient) on each performance parameter (i.e., overall number of passes, passes accuracy percentage, goals allowed, goals conceded, and expected goals). The required assumptions were conducted prior to performing the multiple linear regression and observed high intercorrelations among the predictors of the model. Table 7 presents the computed collinearity diagnostics, which indicated that two of the Variance Inflation Factors (VIF) of network density (*VIF* = 6.03) and average clustering coefficient (*VIF* = 4.95) are fairly large. A viable solution to ameliorate the multicollinearity includes the removal of some of the violating predictors from the model (Mason & Perreault, 1991). Considering the theoretical elaborateness of average clustering coefficient (i.e., computation based on triad connections) compared with network density (i.e., computation based on dual connections), network density was finally omitted from the model. That is, the adjusted regression model consists of five reliable predictors, including closeness centrality, betweenness centrality, weighted in-degree centrality, weighted out-degree centrality, and average clustering coefficient. The required assumptions were rechecked prior to the conduction of the multiple linear regression analyses and were found satisfied. Due to the exploratory nature of this study, five separate stepwise multiple regressions were conducted to estimate the accounted variance of performance outcomes by the SNA coefficients' variances. The results of the multiple regression analysis are presented in Table 8.

Table 7
Computed collinearity diagnostics among the predictors

	First Diagnostics		Second Diagnostics	
Variables	Tolerance	VIF	Tolerance	VIF
Closeness Centrality	.49	2.05	.44	2.25
Betweenness Centrality	.54	1.85	.54	1.86
Weighted in-degree centrality	.67	1.49	.73	1.37
Weighted out-degree centrality	.67	1.48	.75	1.32
Network density	.17	6.03	**	**
Avg. Clustering Coefficient	.20	4.95	.51	1.98

Table 8
Stepwise Multiple regression analyses predict the variances of overall number of accurate passes, passes accuracy percentage, goals allowed, goals conceded, and expected goals, based on the indices of centrality and density

Variables	Overall Number of Accurate Passes		Passes Accuracy percentage		Goals Allowed		Goals Conceded		Expected goals	
	Beta	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*	*Beta*	*t*
Avg. Clustering Coefficient	.56	9.58 **	.48	6.28 **	.31	3.70 **	-.41	-5.25 **	.37	4.61 **
Weighted out-degree centrality	.15	2.11 *	.13	1.82	.08	.97	-.03	-.34	.05	.66
Closeness Centrality	-.08	-1.04	-.12	-.1.3	-.14	-1.40	.16	1.72	-.03	-.27
Betweenness Centrality	-.11	-1.36	-.08	-.92	-.04	-.47	.01	.10	-.08	-.88
Weighted in-degree centrality	-.002	-.02	-.05	-.72	-.07	-.81	.04	.61	-.002	-.03

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

The results of the regression indicated that weighted out-degree centrality and average clustering coefficient significantly accounted for 33% in the variance of overall number of accurate passes, F (2,129) = 33.29, p = .001, R^2= .34, adjusted R^2 = .33. Closer examination of the β weights revealed that average clustering coefficient significantly predicted the overall number of passes (β = .56, t = 9.58, p =.001), as did weighted out-degree centrality (β =.15, t = 2.11, p =.03). However, closeness centrality (p = .32), betweenness centrality (p = .18), and weighted in-degree centrality (p = .98) failed to predict variation in the overall number of accurate passes.

According to the second stepwise multiple regression, the only significant predictor of the passes accuracy percentage was average clustering coefficient (β = .48, t = 6.28, p = .001), which significantly accounted for approximately 23% in the variance in passes accuracy percentage, F(1,130) = 39.46, p = .001, R^2= .233, adjusted R^2 = .227. The contribution of weighted out-degree centrality to the variation in passes accuracy percentage approached significance (p = .07), but not for closeness centrality (p = .19), betweenness centrality (p = .35), and weighted in-degree centrality (p = .47).

Accounting for nearly 9% in the variability of goals allowed F(1,130) = 13.75, p = .001, R^2 = .096, adjusted R^2 = .089, only average clustering coefficient (β =.31, t = 3.70, p =.001) yielded significant contribution to the variance in this performance outcome. As noted, the variance in goals allowed was not accounted for by the other predictors of weighted out-degree centrality (p = .33), closeness centrality (p = .16), betweenness centrality (p = .63), and weighted in-degree centrality (p = .42).

Average clustering coefficient (β = -.41, t = -5.24, p =.001) accounted for approximately 17% in the variance of goals conceded, F(1,130) = 27.50, p = .001, R^2 = .175, adjusted R^2 = .168.

In contrast, weighted out-degree centrality (p = .73), closeness centrality (p = .11), betweenness centrality (p = .92), and weighted in-degree centrality (p = .61) failed to significantly contribute to the prediction of goals conceded.

Only average clustering coefficient (β = .37, t = 4.61, p =.001) significantly accounted for the variance in expected goals, which was nearly 13%, F (1,130) = 21.65, p = .001, R^2 = .141, adjusted R^2 = .134. However, the remaining coefficients in the model, weighted out-degree centrality (p = .51), closeness centrality (p = .78), betweenness centrality (p = .38), and weighted in-degree centrality (p = .97), failed to significant account for the variation in expected goals.

Coordinative Differences Among World-Class Elite Teams

Multivariate Analysis of variance (MANOVA). The second research hypothesis assumed that when world-class elite teams play against each other, they will present relatively similar shared patterns of centrality ratings, density ratings, passes indices, and performance. To test this hypothesis, the centrality, density, and performance variables were calculated in separate clusters, and a dummy variable of match outcome was created to differentiate among world-class elite teams who won to those who did not win (1= win, 0= no win). Previous soccer studies used this distinction since draw and loss are highly correlated with each other compared to draw and win (Kite & Nevill, 2017). Accordingly, it is hypothesized that the differences between the world-class elite teams who won those who did not win on the clusters and single indicators will be non-significant. One-way MANOVAs followed by one-way ANOVAs were calculated to test differences among the world-class elite teams when playing against each other. As such, the dummy coded variable was treated as the independent variable, while the dependent variables were the four centrality coefficients (i.e., closeness centrality, betweenness centrality, weighted in-degree centrality, and weighted out-degree centrality), two density indices (i.e., network density and average clustering coefficient) two passing indices (i.e., overall number of passes and accurate passes percentage), and three performance outcomes (i.e., goals allowed, goals conceded, and expected goals).

Centrality Cluster. Levene's test of equality of variance indicated nonsignificant variations in the centrality indices. Applying the Wilks' Lambda test, a one-way MANOVA revealed nonsignificant differences among the world-class elite teams for the centrality cluster, Wilks' λ = .995, $F(4, 55)$ = .07, p = .99, $\eta 2$= .005. Namely, the teams did not differ in centrality coefficients, whether they won or not. The univariate analysis alongside means and SDs are shown in Table 9.

Table 9
Means, SDs, and ANOVAs for centrality cluster as a function of game outcome among world-class elite teams

	Match Outcome						
	Win (n=22)		No Win (n=38)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1.Closeness Centrality	.73	.14	.71	.15	.16	.003	.14
2. Betweenness Centrality	.04	.02	.04	.01	.001	.001	.00
3. Weighted in-degree centrality	.57	.18	.59	.19	.10	.002	.11
4.Weighted out-degree centrality	.70	.22	.72	.18	.11	.002	.10

Density Cluster. Levene's test of homogeneity was conducted among the density indices and produced homogeneous data (p > .05). A one-way MANOVA revealed nonsignificant differences among the world-class elite teams for the density cluster, *Wilks'* λ = .955, F (2, 57) = 1.34, p = .27, η^2= .04. The univariate analysis alongside means and SDs are shown in Table 10.

Table 10
Means, SDs, and ANOVAs for density cluster as a function game outcome among world-class elite teams

	Match Outcome						
	Win (n=22)		No Win (n=38)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Network Density	.70	.11	.67	.12	1.05	.01	.26
2. Avg. Clustering Coefficient	.74	.09	.69	.12	2.70	.04	.47

Passes Cluster. Levene's test of equality of variance indicated nonsignificant variations in the passes' variables. A one-way MANOVA did not yield significant differences for the passes cluster among the world-class elite teams who won to the world-class elite teams who did not win, Wilks' λ = .974, F(2, 57) = .76, p = .47, $\eta 2$= .03. The univariate analysis alongside means and SDs are shown in Table 11.

Table 11
Means, SDs, and ANOVAs for passes cluster as a function game outcome among world-class elite teams

	Match Outcome						
	Win (n=22)		No Win (n=38)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Overall Number of Accurate Passes	452	123	411	151	1.58	.02	.30
2. Accurate passes percentage	.85	.04	.84	.05	1.52	.02	.22

Performance cluster. Levene's test for homogeneity of variances proved statistically significant differences for goals allowed (Levene's test, $F = 11.25$, $p = .001$), goals conceded (Levene's test, $F = 6.54$, $p = .01$), and expected goals (Levene's test, $F = 4.13$, $p = .05$). Using the Pillai's trace test, the one-way MANOVA indicated statistically significant differences for the performance cluster between the world-class elite teams who won to those who did not win, *Pillai's trace* = .425, F (3, 56) = 25.27, $p < .001$, $\eta 2 = .58$. The univariate analysis alongside means and SDs are shown in Table 12.

Table 12
Means, SDs, and ANOVAs for performance cluster as a function game outcome among world-class elite teams

	Match Outcome						
	Win (n=22)		No Win (n=38)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Goals Allowed	2.68	1.42	.74	.72	49.19**	.46	1.72
2. Goals Conceded	.73	.68	1.87	1.50	10.88**	.16	.97
3. Expected Goals	1.75	.76	1.03	.54	18.34**	.24	1.09

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

A one-way ANOVA revealed a significant team effect in goals allowed, $F (1,58) = 49.19$, $p = .001$, $\eta_p^2 = .46$, indicating that the world-class elite teams who won scored more goals than the world-class elite teams who did not win (M =2.68, SD = 1.42 vs M = .74, SD = .72; d = 1.72). Likewise, a significant performance effect emerged for goals conceded, $F(1,58) = 10.88$, p = .002, $\eta_p^2 = .16$, indicating that winning world-class teams allowed less goals than world-class elite teams who did not win (*M* =.73, *SD* = .68 vs *M* = 1.87, *SD* = 1.50; *d* = .97). Additionally, the univariate analysis for expected goals parameter was significant, F (1,58) = 18.34 , p = .001, η_p^2 = .24, meaning that winning world-class elite teams displayed higher probabilities to score goals over the world-elite teams who did not win (*M* = 1.75, *SD* = .76 vs *M* = 1.03, *SD* = 1.54; *d* = 1.09).

Coordinative Differences Within Competitive-Elite Teams

The third research hypothesis assumed that competitive-elite teams would present relatively similar patterns of centrality ratings, density ratings, passes indices, and performance. To test this hypothesis, the centrality, density, passes, and performance parameters were calculated within separate clusters, and a dummy variable of match outcome was created to differentiate among the competitive-elite teams with respect to the games' outcomes - win or did not win (1= win, 0= no win). Consequently, it was assumed that the differences among the competitive-elite teams who won to those who did not win would be non-significant for each cluster and single indicator. One-way MANOVAs followed by one-way ANOVAs were carry out to test the coordinative differences among the competitive-elite teams. In that case, the dummy coded variable was treated as the independent variable, while the dependent variables were the four centrality coefficients (i.e., closeness centrality, betweenness centrality, weighted in-degree centrality, and weighted out-degree centrality), two density indices (i.e., network density and average clustering coefficient) two passing indices (i.e., overall number of passes and accurate passes percentage), and three performance outcomes (i.e., goals allowed, goals conceded, and expected goals). Frequency distribution charts are presented to further elaborate on the relative centrality and density patterns within the competitive-elite teams (see Appendix B- Frequency Distribution Charts Within Competitive-Elite Teams). Visual inspection of the curves suggests that the majority of the distributions are approximately normal. The competitive-elite teams showed relatively similar proportions of closeness and betweenness centrality. Akin with previous studies, the algorithm implementation of betweenness centrality ranges from 0 to 0.1 (Overbury, Kiss, & Berthouze, 2018). The graphs of weighted-in-and-out degree centrality implied high values of centrality, meaning that the competitive-elite teams tend to rely on a few players in their passing strategy. Likewise, the relative concentration of the density variables (i.e., network density and average clustering coefficient) were between 0.5 to 0.8, signifying medium-to-high density distributions within the competitive-elite teams.

While Levene's test of error variances indicated nonsignificant variations for the coefficients of closeness centrality, betweenness centrality, and weighted out-degree centrality, it proved statistically significant differences for weighted in-degree centrality (Levene's test, $F = 7.75$, $p = .009$). Using the Pillai's trace test, a one-way MANOVA did not yield significant differences for the centrality cluster among the competitive-elite teams who won to the competitive-elite teams who did not win, *Pillai's trace* = .083, $F(4, 31) = .69$, $p = .59$, $\eta 2 = .08$. The univariate analysis alongside means and SDs are shown in Table 13.

Table 13
Means, SDs, and ANOVAs for centrality cluster as a function of game outcome within competitive-elite teams

	Match Outcome						
	Win (n=7)		No Win (n=29)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1.Closeness Centrality	.71	.10	.73	.08	.58	.02	.22
2. Betweenness Centrality	.03	.01	.04	.01	.35	.01	1.00

Table 13 continued

3. Weighted in-degree centrality	.52	.06	.59	.19	.92	.03	.49
4.Weighted out-degree centrality	.66	.18	.69	.19	.12	.004	.16

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

Density Cluster. Levene's test of equality of variance indicated nonsignificant variations in the density indices. A one-way MANOVA revealed nonsignificant outcome differences among the competitive-elite teams for the density cluster, *Wilks'* $\lambda = .993$, $F\ (2, 33) = .12$, $p = .89$, $\eta^2 = .007$. The univariate analyses alongside means and SDs are shown in Table 14.

Table 14
Means, SDs, and ANOVAs for density cluster as a function game outcome within competitive -elite teams

	Match Outcome						
	Win (n=7)		No Win (n=29)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Network Density	.62	.15	.59	.14	.24	.007	.21
2. Avg. Clustering Coefficient	.65	.15	.62	.13	.18	.005	.21

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

Passes Cluster. Levene's test of equality of error variances was not significant for passes cluster. Applying the *Wilks' Lambda* test, a one-way MANOVA revealed nonsignificant differences among the competitive-elite teams for the passes cluster, *Wilks'* $\lambda = .973$, $F\ (2, 33) = .46$, $p = .64$, $\eta^2 = .03$. The univariate analysis alongside means and SDs are shown in Table 15.

Table 15
Means, SDs, and ANOVAs for passes cluster as a function game outcome within competitive -elite teams

	Match Outcome						
	Win (n=7)		No Win (n=29)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Overall Number of Accurate Passes	280	112	252	93	.48	.01	.28
2. Accurate passes percentage	.80	.05	.78	.06	.92	.03	.36

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

Performance Cluster. Levene's test of homogeneity was conducted among the performance indices and produced homogeneous data ($p > .05$). A one-way MANOVA yield a significant difference among the competitive-elite teams for the performance cluster, *Wilks'* λ = .504, F (3, 32) = 10.48, $p < .001$, η^2= .49. The univariate analysis alongside means and SDs are shown in Table 16.

Table 16
Means, SDs, and ANOVAs for performance cluster as a function game outcome within competitive-elite teams

	Match Outcome						
	Win (n=7)		No Win (n=29)				
Variable	Mean	SD	Mean	SD	F	η^2	*d*
1. Goals Allowed	.71	.69	.38	.62	1.50	.04	.50
2. Goals Conceded	.86	.89	3.34	1.69	13.90**	.29	1.83
3. Expected Goals	.78	.38	.76	.53	.02	.001	.04

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

Subsequent univariate analyses applied for the performance cluster revealed significant outcome effect within competitive-class elite teams who won to those who did not win, epitomized by the variable of goals conceded, $F\ (1{,}34) = 13.90$, $p = .001$, $\eta_p^2 = .29$. Specifically, the winning competitive-elite teams conceded less goals than the competitive-elite teams who did not win (M =.86, SD =.89 vs M = 3.34, SD = 1.69; d = 1.83), However, there were non-significant differences among the competitive-elite teams in the other performance indices, goals allowed (p = .23), and expected goals (p = .90).

CHAPTER FOUR

DISCUSSION

The current study utilized the Game-Based Interaction Networks (GBIN) method to uncover synthesizing team coordination mechanisms of elite soccer teams. Given the scarcity of research examining coordination during actual sport competitions (Eccles, 2010), modeling these interactions serves as a phenomenon of interest. In sport, environmental and task constraints direct individuals to coordinate their actions in space and time to achieve performance goals (Silva et al., 2016). Predicated on these concepts, the inquiry of sports performance through an ecological dynamics approach pertains to how repeated interactions among athletes result in the emergence of self-organizing patterns of behavior (Araújo et al., in press). Contrary to approaches that emphasize mental representations to study team coordination, the ecological dynamics approach concentrates on analyzing the actions themselves, since they represent "true cognitive behaviors" in naturalistic performance contexts (Araújo et al., 2019, p.7). Inclusively, uncovering the underlying conditions where teammates are more likely to display efficient coordination patterns may address essential barriers and facilitators of performance of sport teams (Gray et al., 2017).

The Social Network Analysis (SNA) has become a prominent tool in social sciences due to its advanced algorithms that illustrate and quantify collective patterns of organisms in their naturistic environments (Batool & Niazi, 2014). In the last decade, this method has been applied in sport studies to explore crucial team properties in the form of cohesion (Anderson & Warner, 2017), leadership (Fransen et al., 2015), and communication (Mclean et al., 2019). Based on the principles of the SNA approach, the Game-Based Interaction Networks (GBIN) method conceptualizes sport teams as networks, where the ties (e.g., passes) among teammates reflect self-organizing tendencies (Wäsche et al., 2017). Network metrics of centrality and density were found as effective characteristics to determine the cooperation behaviors of sport teams when preforming in open task environments (Grund, 2012). Nonetheless, while only a few studies examined this method in the domain of soccer, these studies neglected important contextual variables, such as a comparison among teams at different stages of expertise during a relatively consistent time frame of a season league.

The current study included 66 soccer matches from the La-Liga Spanish league, English Premier League, and German Bundesliga. Aligned with the standardized taxonomy of expertise in sport, I examined 36 direct matches between world-class elite teams to competitive elite-teams. In addition, the current study consisted of 30 matches among world-class elite teams, and 36 matches of competitive-elite teams. The findings suggest that world-class elite teams showed a greater extent of decentralized patterns, density coefficients, passes accuracy benchmarks, and performance outcomes than the competitive-elite teams. However, world-class elite teams and competitive-elite teams did not differ in the indices of weighted in-degree and weighted out-degree centrality. Moreover, multiple linear regression analyses were applied to test the predictive power of the coefficient factors (i.e., betweenness centrality, closeness centrality, weighted in-degree centrality, weighted out-degree centrality, and average clustering coefficient) on each performance criterion. The results of the regression indicated that both, average clustering coefficient and weighted out-degree centrality, significantly accounted for 33% of the variance of overall number of passes, and that average clustering coefficient accounted for 23% of the variance of passes accuracy percentage, 9% of the variability in goals allowed, approximately 17% of the variance in goals conceded, and nearly 13% of the variability in expected goals. In addition, an examination of games among world-class teams indicated differences only for performance outcomes. However, the teams presented commonality concerning the other centralities, density, and passes coefficients. Likewise, one-way MANOVAs revealed relatively similar coordination patterns among the competitive-elite teams.

Hypothesis 1: Coordinative and performance differences among world-class elite teams and competitive-elite teams

The findings support the first hypothesis. World-class elite teams demonstrated greater levels of coordinative patterns that were expressed through higher closeness centrality, lower betweenness centrality (i.e., centrality), higher intra-team connectivity (i.e., density), superior accurate passes factors, and greater performance outcomes than competitive-elite teams. Nevertheless, there were no apparent differences between world-class elite teams and competitive-elite teams on the indices of weighted in-degree centrality and weighted out-degree centrality. Furthermore, the multiple linear regression analyses revealed that both average clustering coefficient and weighted out-degree centrality were significant predictors of the outcomes of the overall number of accurate passes (33%). Moreover, only average clustering coefficient significantly contributed to the explained variance of passes accuracy percentage (25%), goals allowed (9%), goals conceded (20%), and expected goals (12%).

A one-way MANOVA revealed that world-class elite teams maintained higher closeness centrality than the competitive-elite teams, indicating that the former displayed greater tendencies to reach each other more easily in the passing networks. Moreover, epitomized by the betweenness centrality variable, the results showed world-class elite teams' players tend to be more involved to create efficient fluidity of the ball than the competitive-elite teams' counterparts. Studies using GBIN in soccer showed that successful teams are more likely to maintain high closeness centrality and low betweenness centrality (i.e., Clemente et al., 2015). An integrative view on our findings, alongside previous investigations, points to the possibility that when teams are less dependent on specific players, they maintain a balanced passing strategy. This coordinative behavior is reflected by a team effort to pass the ball between a relatively large number of players, making it difficult for the opponent to block a decentralized passing pattern. The decentralized passing patterns seem to play an integral role in the structural actions of world-class elite teams, as it may indicate that these teams are characterized by distinct functions to achieve superior performance. As opposed to relying on a single ready-made solution, cooperative synergy can execute adaptable behaviors more efficiently according to fluctuations in the performance environment and the task demands (Seifert et al., 2016). Essentially, adaptive synergy behaviors are strongly related to beneficial performance in sport (Bourbousson, et al., 2010). Taken together, these findings suggest that the quality of high-caliber sport teams is associated with a distributed passing strategy versus counting on one or just a few specific players.

Nevertheless, the statistical value of weighted in-degree centrality was not found to distinguish between world-class teams and competitive-elite teams. In addition, the weighted out-degree centrality failed to produce any effect on the differences associated with team caliber. These findings align with previous soccer studies that showed no differences between teams on these two indices (Grund, 2012; Clemente et al., 2015). In his seminal paper, Grund (2012) speculated that when teams play well and score early in the match, they may switch to a different mode of playing more defensively. Therefore, the players are less likely to show affordances for receiving and delivering the ball as they focus on the defensive efforts. As pertains to the latter concept, Clemente and colleagues (2015) inquired contextual patterns of four world-class elite national teams in 2014 FIFA World cup. The researchers found increased weighted-in-and-out-degree centrality scores between the first half and the second half, which corroborated the claim of Grund (2012). Pertaining to our results, it is feasible to assume that the world-class elite teams display similar tendencies not only at short-term international tournaments but also throughout a time frame of a season league.

The current investigation shows that world-class elite teams displayed higher network density and average clustering coefficient than competitive-elite teams. This finding illustrates the prevalence of a high interdependence among world-class elite teams' members, while indicating lesser connectivity among players in competitive-elite teams. These findings are in line with previous studies in soccer that showed an association between high-density networks and superior performance and between low-density networks and inferior performance (i.e., Pina et al., 2017). A dense system consists of many reciprocal connections among teammates which are likely to facilitate the coordinating efforts to reach task goals (Reimer et al., 2006). In contrast, in teams that are characterized as more isolated, teammates may struggle to synchronize their actions, hence may be more likely to experience coordination breakdowns, resulting in performance deterioration (Gonçalves et al., 2017).

The MANOVAs showed that world-class elite teams outperformed the competitive-elite teams on passes accuracy parameters (i.e., overall number of accurate passes and passes accuracy percentage). This finding corresponds with basic constructs of the ecological dynamics approach. The concept of 'skilled intentionally' (Kiverstein & Rietveld, 2015) describes highly skilled organisms with the equipped ability to choose among diverse possibilities for actions. Proficient players are more efficient in extracting relevant context-dependent information from the environment, which assists them in attuning their behaviors with each other more accurately (Feigean et al., 2018). In turn, when coupled together, world-class elite team players maximize the existence of these opportunities with the execution of more refined actions.

Akin to the first hypothesis, world-class elite teams showed a greater level of performance as indicated by their tendency to score more goals and concede fewer goals than the competitive-elite teams' counterparts. Additionally, world-class elite teams showed a higher quality of goal shots as indicated by a higher rating of expected goals (XG). Namely, in these teams, players created better opportunities to score goals compared to players in the competitive-elite teams. These findings correspond with previous GBIN studies that showed that the profile of high-density and decentralized teams was associated with better performance (i.e., Grund, 2012). Now, the ecological dynamics research is limited in predicting the conditions under which individuals are better able to coordinate their movements with each other (Araújo et al., 2019). Together with the innovative trend of alteration of performance studies from a mainly qualitative framework towards quantitative and algorithm-based analysis, scholars can utilize advanced team properties that influence team performance (Pina et al., 2017). Specifically, the current investigation provides support for the following process chain: coordination is underlined in soccer by centrality, density, and passes indices, which in turn, impact the level of performance that is defined by actual goals and expected goals.

Multiple regression analyses were used to examine the extent to which the chosen SNA factors influenced the passes and performance outcomes. The analysis revealed that higher average clustering coefficient and weighted in-degree centrality significantly predicted greater overall number of passes (33%), and that higher clustering coefficient significantly predicted passes accuracy percentage (25%), goals conceded (17%), and greater actual goals (9%) and expected goals (13%). Inclusively, these findings ascertain that average clustering coefficient is a powerful predictor for team performance. Such results are consistent with previous research, which has demonstrated that average clustering coefficient accounted for more of the variance in team performance during the 2018 FIFA World Cup compared with the other SNA measures (Aquino et al., 2019). While higher weighted out-degree centrality was affiliated with an increased overall number of accurate passes, this coefficient was not accounted for the variance of the other performance outcomes. As discussed above, weighted out-degree and weighted in-degree centralities are more susceptible to contextual considerations (i.e., increased scores in the second half; Clemente et al., 2015); this pattern may explain their nonsignificant contribution in predicting team performance. While the variables of closeness centrality and betweenness centrality showed differences among world-class elite teams and competitive-elite teams, they did not contribute to the variations in performance outcomes. It is suggested that the computational loads of these variables are relatively small, resulting in a minor influence on the overall model (Baglioni et al., 2012). Overall, estimating how the various SNA measures impact the specific passes and performance outcomes can guide further applied and theoretical exploration of GBIN in actual soccer environments.

Hypothesis 2: Coordinative differences among world-class elite teams

The second hypothesis was confirmed. Our findings indicated that when played against each other, world-class elite teams showed similar patterns of centrality, density, and passes, whether they won or did not win. As the comparison of winning versus not winning embodies a different level of performance, the world-class elite teams showed differences in the quality of performance (i.e., goals scored, goals conceded, and expected goals).

Aligned with previous GBIN investigations, teams that meet the requirements for the standardized expertise taxonomy of world-class elite teams, tend to show high and similar levels of connectivity and coordination (Clemente et al., 2015). Observations of these patterns were also prominent in our analyses of visual networks. Respectively, visual configurations of coordination patterns among world-class elite teams tend to show mutual models of highly connected distributed networks. These findings may be explained by the fact that world-class elite teams are at the highest stage of expertise, hence sharing adaptive structured coordination strategies that underline top performance (Araújo et al., 2019). For instance, past investigation of the self-organizing mechanisms of Barcelona has shown that the linear combination of density and pass precision may explain the superiority of this world-class elite team (Chassy, 2013). The author attributed the unique passing style of Barcelona to several tactical and psychological mechanisms. Fundamentally, Barcelona players practice together several years before performing at the top professional club team, emphasizing the role of collective experience with regards to underlying successful passing strategy. Furthermore, specific characteristics in the form of athletes' skills facilitate the exertion of functional affordances which guides the embodiment of precise joint actions (Araújo et al., in press).

Hypothesis 3: Coordinative differences among competitive-elite teams

The third hypothesis was confirmed. The MANAOVAs indicated that competitive-elite teams showed relatively similar patterns of centrality, density, passes, and performance, whether they won or did not win. These teams only differed by the performance outcome of goals conceded, emphasizing the worth of defensive efficiency (i.e., preventing goals) compared to offensive outputs (i.e., goal-scoring) among teams at lower stages of expertise (Boscá, Liern, Martínez, & Sala, 2009). Previous SNA study found that teams with similar performance outcomes tend to show similar social network topology (Wise, 2014). Specifically, lower-ranked teams are more likely to be “riddled with structural holes (p. 710)”, which ultimately, results in deteriorated performance outcomes. These patterns were visible in our network configurations. Ecological dynamics approach scholars theorized that less-skilled performers are exposed to limited “field of the affordances (Araújo et al., 2019, p.16),” which minimize adaptive capacities of performance. Altogether, the potential task solutions of competitive-elite teams rely on a relatively scant number of affordances, embodied by certain similarities.

Limitations, Future Directions, and Implications

While the findings supply evidence for distinctive coordinative patterns among soccer teams at different stages of expertise, one should be aware of the potential limitations of this study. The first concern pertains to the sampling of the teams in this study, which limits the generalizability of the results. The dataset captured the network characteristics of senior competitive soccer teams from the top professional men’s leagues in Spain, England, and Germany. This does not prove that the current findings reflect other soccer populations. To minimize this gap, future GBIN studies must incorporate an inclusive approach that considers samples from various backgrounds, such as women’s soccer, low-skilled teams, and youth populations. For instance, a previous study utilized the GBIN method in a friendly (i.e., training) match between under-15 and under-17 age groups (Gonçalves et al., 2017). While this study revealed coordinative variations among teams in different age groups, it has relied on one specific game in an uncompetitive environment. Simultaneously, extending the GBIN method into other sports (e.g., Australian Football; Young, Luo, Gastin, Lai, & Dwyer, 2019) may augment the generalizability power of future research.

When it comes to conceptual limitations, this study neglected the players' off-the-ball-movements. Tactically oriented team sports, such as soccer, include dimensions where players coordinate their actions according to the off-ball-movements of their teammates. This is a common problem when exerting the method of GBIN into soccer (Mclean et al., 2019). While this study utilized knowledge based on Global Positioning Systems (GPS) to capture the average location of players during matches, advanced technologies, such as the Motion Analysis System, could be useful in coding various coordinated off-the-ball movements during actual games (Carling, Bloomfield, Nelsen, & Reilly, 2008). Alternatively, propagating the GBIN method can be done by assimilating a play-by-play network analysis in soccer. Innovative metrics have been proposed to capture each sequence of passes in an attacking play, while simultaneously defining weights based on the outcome of each interaction (Korte, Link, Groll, & Lames, 2019). Hypothetically, sequences that result in a successful outcome (i.e., entering into the finishing zone, gaining a free kick, shooting, and scoring) are scored higher compared to unsuccessful events, where the team loses the ball possession before entering into the finishing zone. The authors encouraged other scholars to invent new parameters that reflect definite patterns of coordination. For instance, they proposed that 'betweenness centrality' will be transformed into 'flow betweenness,' which aggregates the ball-fluidity scores in each interaction while considering the outcome of these sequences.

Gonçalves and colleagues (2017), suggested potential contextual variables that should be considered when utilizing the GBIN exploratory method. While the quality of the league, level of opponent, game status, and game score are perceived as obvious contextual variables in sport, the game location was considered in the recent years as a paramount factor to influence the probability of success. A meta-analysis showed a definite home-field advantage in ten different sports ($P_{\text{home win}}$ = .604) with a significant home advantage in soccer ($P_{\text{home win}}$ = .674) above the other sports (Jamieson, 2010). Possible mechanisms that might benefit the home teams are ascribed to the supportive behavior of the home fans (Jamieson, 2010), referee bias (Pollard, 2008), and a familiarly with visual cues (Barnett, & Hilditch, 1993). Thus, future GBIN studies should consider the integration of these controlling variables.

Another conceptual concern pertains to the experience of perceived coordination by the players. This study used the method of GBIN to capture objective measures of team coordination without addressing any subjective experiences of the players themselves. Since GBIN consists of measuring actual relations, and most of the traditional instruments are based on general attitudes, this integration may improve the validity of core concepts in the field of sport and exercise psychology (Anderson & Warner, 2017). For instance, a recent study utilized GBIN, combined with the perceived effectiveness of team communication (Mclean et al., 2019). However, this study consisted of the outcomes of only one specific soccer team. Overall, investigating GBIN alongside with subjective intra-team coordination data may be a valuable methodological approach to extend our knowledge on coordinative mechanisms in sport teams.

The current study formulated the theoretical background for using the GBIN method in studying coordinative patterns of sport teams. As the ecological dynamics approach has been limited by methodologies that capture real-time interactions (Araújo et al., 2019), the current study can guide further theoretical and applied explorations for endorsing the GBIN method as an operational definition of team coordination in the sport. The study builds upon previous postulations to incorporate crucial contextual considerations when assessing the underlying coordination mechanisms of sport teams (Grund, 2012; Gonçalves et al., 2017). Therefore, the study itself is unique in that it relates to the inclusion of a relatively large sample of teams from various leagues, assessing objective team properties during live matches, and facilitating the inquiry via visual configurations. Moreover, the study deployed a standardized taxonomy of expertise to compare among teams at different divisions (Swann et al. 2015). Given the shortage of research examining coordination during live competitions, these findings may reveal the ways in which teams form their passing strategies based on different situational contexts. Practically, coaches and performance consultants may utilize such information for designing practice learning environments, and even to make decisions during matches for the sake of optimizing the link between team coordination and performance.

Conclusions

To conclude, the current study investigated how world-class elite teams and competitive elite-teams in the La-Liga Spanish league, English Premier League, and German Bundesliga differ on coordination and performance indices. These aforementioned findings support the notion that the world-class elite teams operate throughout adaptive synergy behaviors, which leads to an efficient passing strategy that plays a crucial role in outperforming the competitive-elite teams. The study showed world-class elite teams maintained positive and similar coordinative patterns when playing against each other. Likewise, the competitive-elite teams presented similar social network topology. Overall, the findings in the current study can guide further applied and theoretical explorations for endorsing the GBIN method as an operational definition of team coordination in the sport.

APPENDIX A

DESCRIPTIVE STATISTICS DATA

Table 17
Means and visual representations of 3 matches between world-class elite and competitive elite teams

Game 7. Team 1 vs. Team 19 (Spain)

Variable	*Team1*	*Team 20*
Centrality		
Closeness Centrality	.87	.75
Betweenness Centrality	.02	.04
Weighted in-degree centrality	.56	.58
Weighted out-degree centrality	.58	.97
Density		
Network density	.84	.64
Avg. Clustering Coefficient	.88	.71
Passes		
Accurate passes	580	238
Accurate passes percentage	.91	.83
Performance		
Goal Scored	8	2
Goal Conceded	2	8
Expected Goals	4.12	1.12

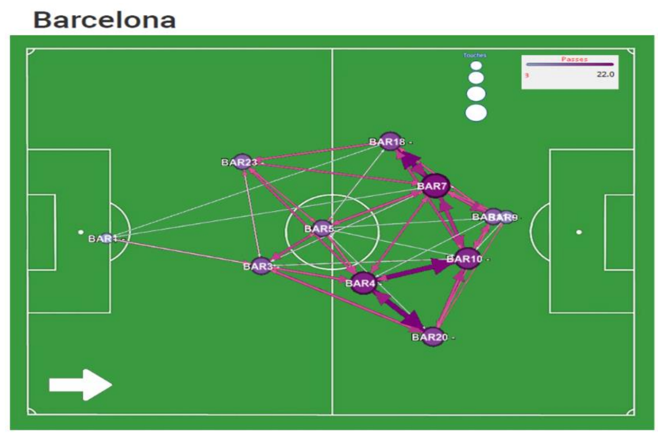

Figure 2.1. Graphic representation of Team 1 vs. Team 19 (Spain)

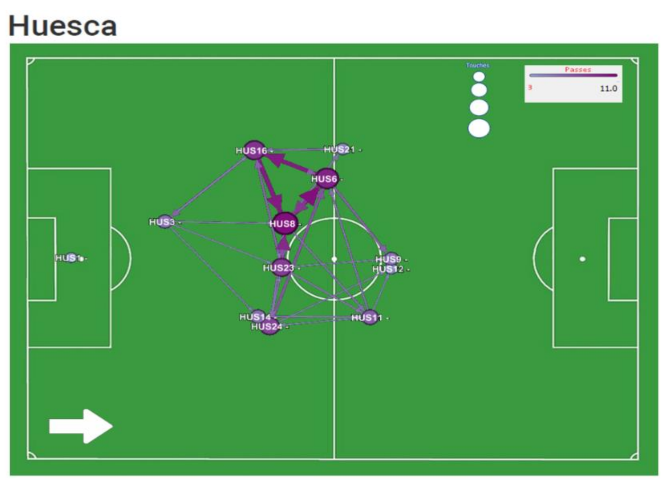

Figure 2.2. Graphic representation of Team 19 vs. Team 1 (Spain)

Table 17 continued

Game 32. Team 20 vs. Team 1 (England)

Variable	*Team20*	*Team1*
Centrality		
Closeness Centrality	.75	.87
Betweenness Centrality	.03	.01
Weighted in-degree centrality	.39	.60
Weighted out-degree centrality	.67	.69
Density		
Network density	.65	.84
Avg. Clustering Coefficient	.65	.86
Passes		
Accurate passes	256	628
Accurate passes percentage	.78	.88
Performance		
Goal Scored	0	3
Goal Conceded	3	0
Expected Goals	0.89	1.78

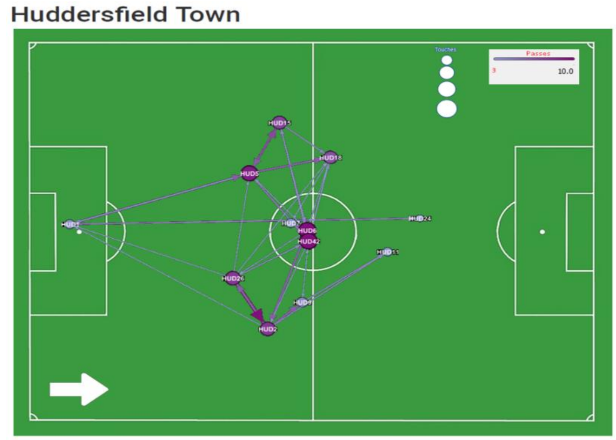

Figure 2.3. Graphic representation of Team 20 vs. Team 1 (England)

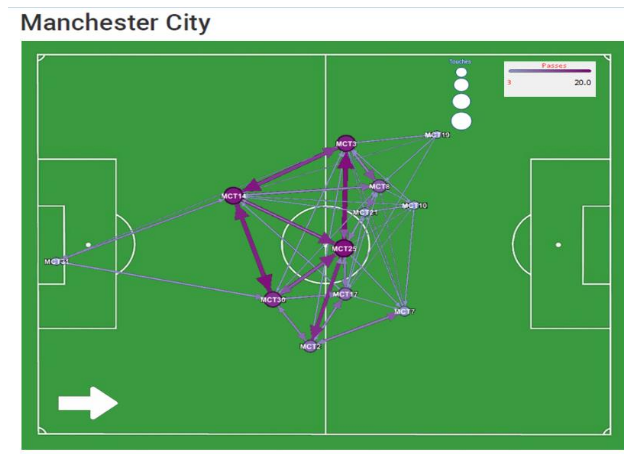

Figure 2.4. Graphic representation of Team 1 vs. Team 20 (England)

Table 17 continued

Game 53. Team 17 vs. Team 1 (Germany)		
Variable	*Team17*	*Team1*
Centrality		
Closeness Centrality	.68	.88
Betweenness Centrality	.04	.02
Weighted in-degree centrality	.53	.43
Weighted out-degree centrality	.71	.61
Density		
Network density	.51	.86
Avg. Clustering Coefficient	.58	.86
Passes		
Accurate passes	214	689
Accurate passes percentage	.78	.88
Performance		
Goal Scored	0	4
Goal Conceded	4	0
Expected Goals	0.78	0.91

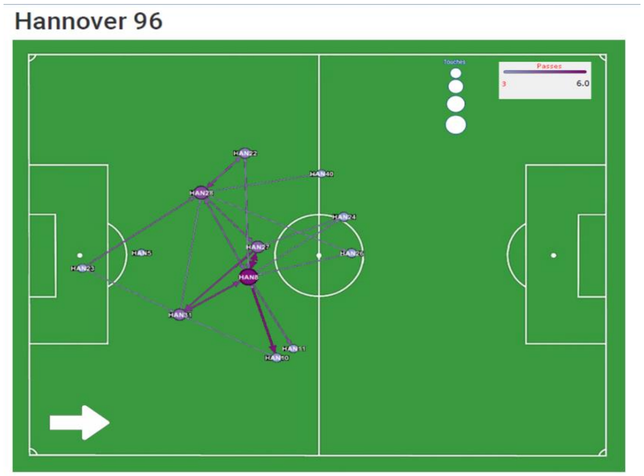

Figure 2.5. Graphic representation of Team 17 vs. Team 1 (Germany)

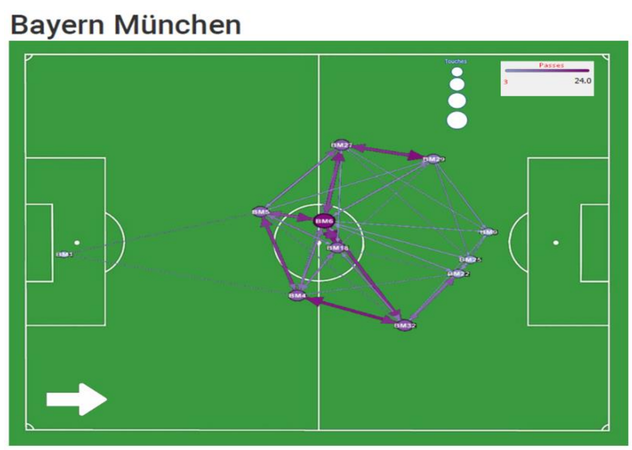

Figure 2.6. Graphic representation of Team 1 vs. Team 17 (Germany)

Table 18.
Means and visual representations of 3 matches among world-class elite teams

Game 5. Team 3 vs. Team 1 (Spain)		
Variable	*Team3*	*Team1*
Centrality		
Closeness Centrality	.75	.85
Betweenness Centrality	.03	.02
Weighted in-degree centrality	.64	.48
Weighted out-degree centrality	.50	.45
Density		
Network density	.62	.82
Avg. Clustering Coefficient	.66	.82
Passes		
Accurate passes	381	438
Accurate passes percentage	.83	.88
Performance		
Goal Scored	0	1
Goal Conceded	1	0
Expected Goals	1.19	0.91

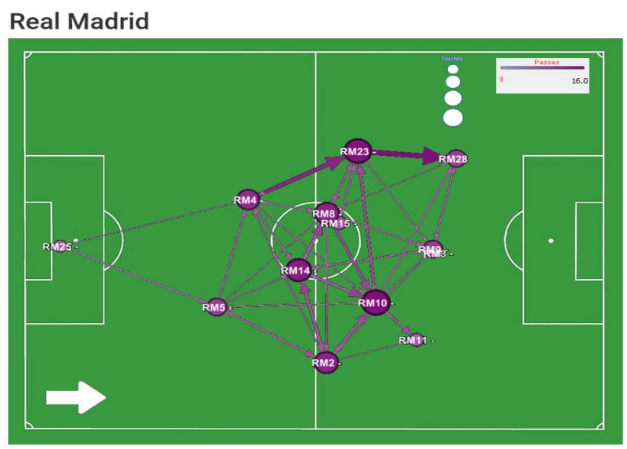

Figure 3.1. Graphic representation of Team 3 vs. Team 1 (Spain)

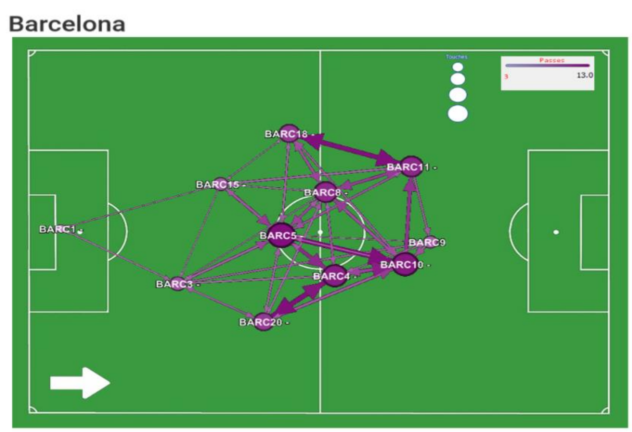

Figure 3.2. Graphic representation of Team 1 vs. Team 3 (Spain)

Table 18 continued

Game 36. Team 3 vs. Team 2 (England)

Variable	*Team2*	*Team3*
Centrality		
Closeness Centrality	.82	.91
Betweenness Centrality	.03	.01
Weighted in-degree centrality	.33	.42
Weighted out-degree centrality	.63	.78
Density		
Network density	.75	.87
Avg. Clustering Coefficient	.80	.90
Passes		
Accurate passes	440	536
Accurate passes percentage	.86	.86
Performance		
Goal Scored	1	1
Goal Conceded	1	1
Expected Goals	1.02	1.88

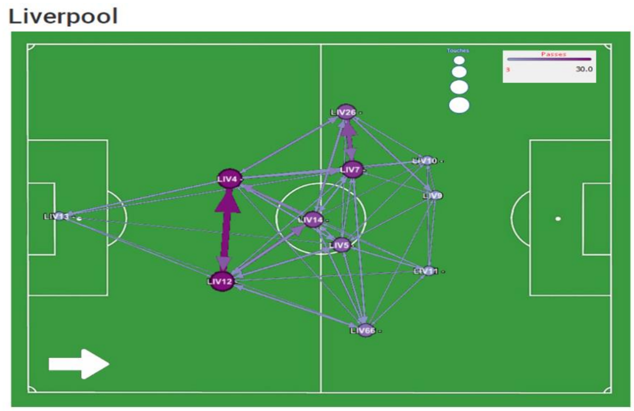

Figure 3.3. Graphic representation of Team 2 vs. Team 3 (England)

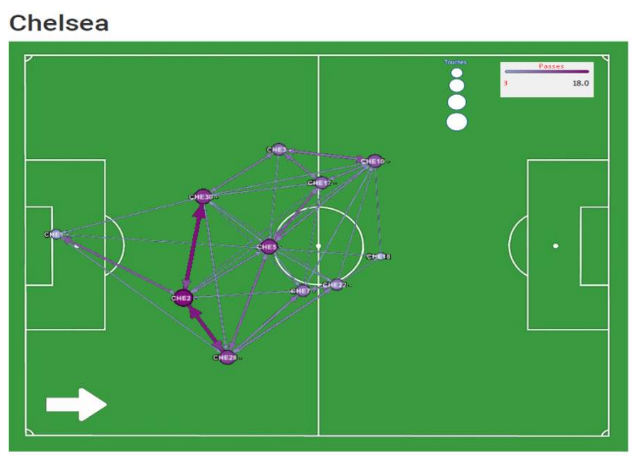

Figure 3.4. Graphic representation of Team 3 vs. Team 2 (England)

Table 18 continued

Game 46. Team 2 vs. Team 1 (Germany)

Variable	*Team2*	*Team1*
Centrality		
Closeness Centrality	.74	.86
Betweenness Centrality	.03	.02
Weighted in-degree centrality	.61	.37
Weighted out-degree centrality	.85	.58
Density		
Network density	.58	.82
Avg. Clustering Coefficient	.65	.81
Passes		
Accurate passes	386	528
Accurate passes percentage	.84	.87
Performance		
Goal Scored	3	2
Goal Conceded	2	3
Expected Goals	2.54	1.52

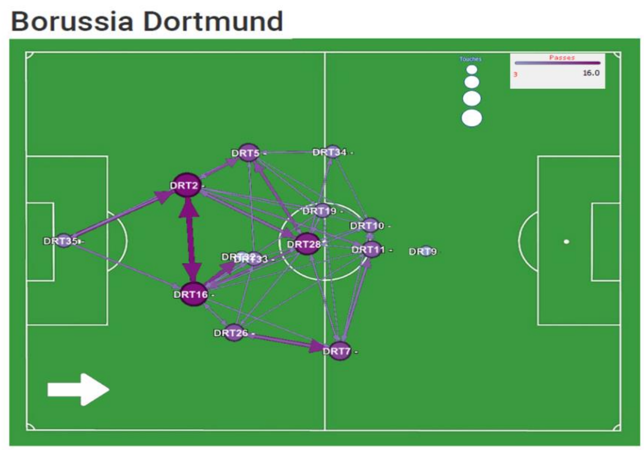

Figure 3.5. Graphic representation of Team 2 vs. Team 1 (Germany)

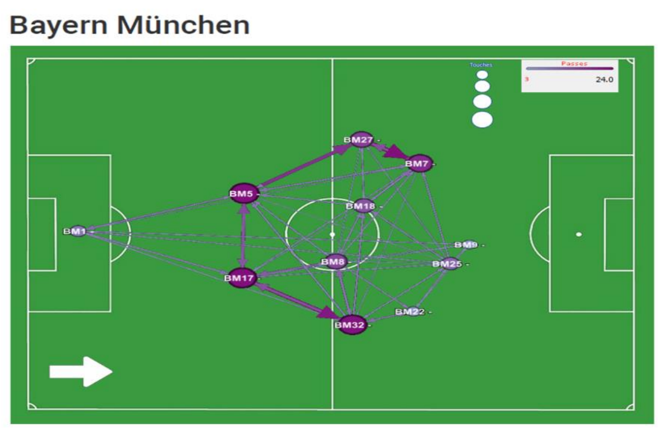

Figure 3.6. Graphic representation of Team 1 vs. Team 2 (Germany)

Table 19

Means and visual representations of three competitive-elite teams

Team 19 (Spain) in game 22, team 19 (England) in game 36, and team 18 (Germany) in game 56

Variable	*Team19*	*Team18*	*Team 18*
Centrality			
Closeness Centrality	.77	.66	.73
Betweenness Centrality	.03	.06	.04
Weighted in-degree centrality	.48	.56	.66
Weighted out-degree centrality	.98	.97	.95
Density			
Network density	.68	.49	.63
Avg. Clustering Coefficient	.72	.54	.62
Passes			
Accurate passes	287	120	181
Accurate passes percentage	.76	.74	.73
Performance			
Goal Scored	0	0	0
Goal Conceded	3	2	3
Expected Goals	1.09	.14	.37

Huesca

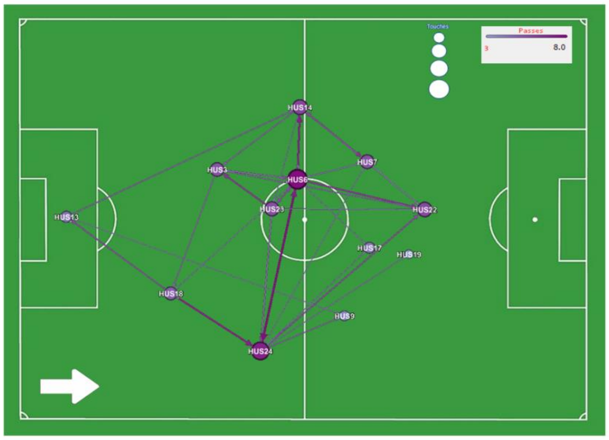

Figure 4.1. Graphic representation of Team 19 (Spain)

Fulham

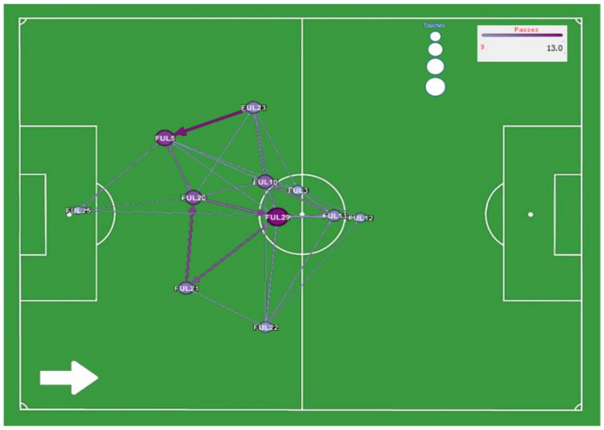

Figure 4.2. Graphic representation of Team 19 (England)

Nürnberg

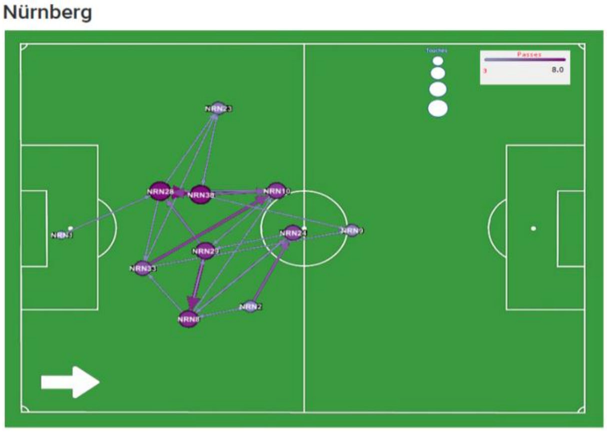

Figure 4.3. Graphic representation of Team 19 (Germany)

APPENDIX B

FREQUENCY DISTRUBUTION CHARTS WITHIN COMPETITIVE-ELITE TEAMS

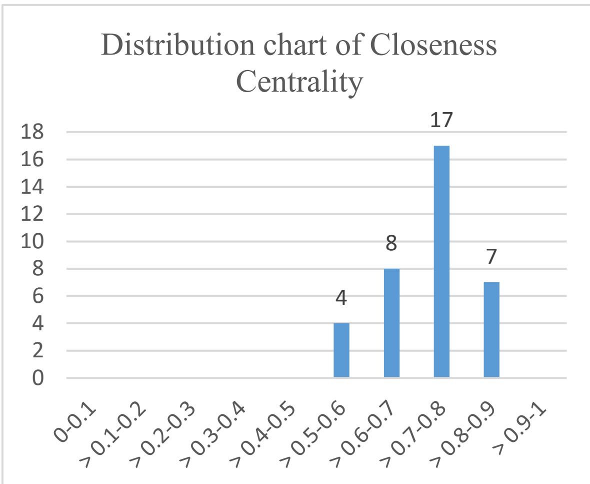

Figure 5.1. Frequency distribution chart of closeness centrality within competitive-elite teams

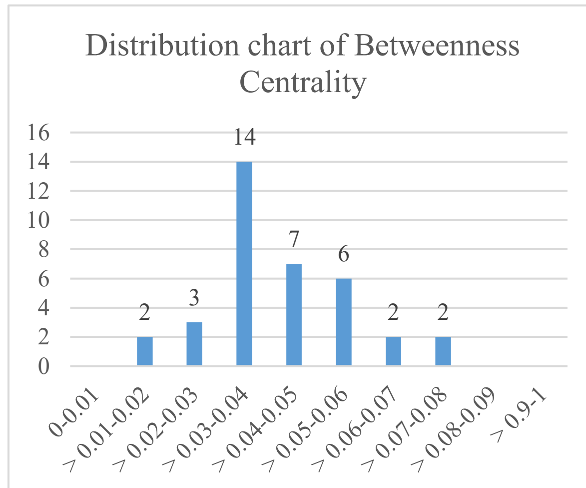

Figure 5.2. Frequency distribution chart of betweenness centrality within competitive-elite teams

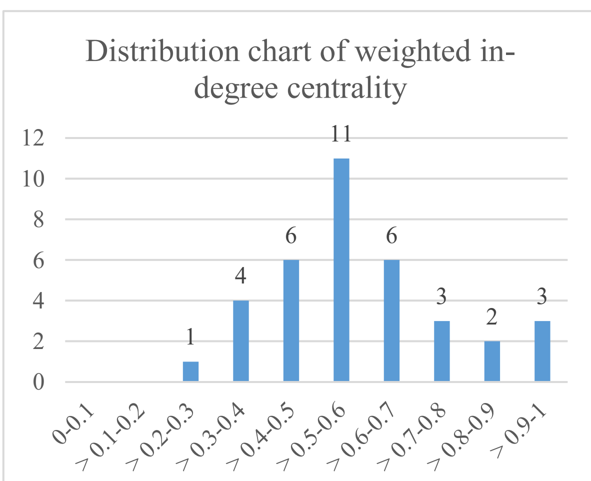

Figure 5.3. Frequency distribution chart of weighted in-degree centrality within competitive-elite teams

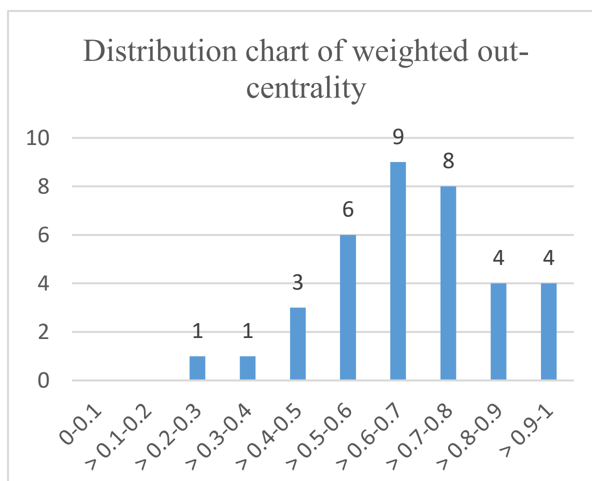

Figure 5.4. Frequency distribution chart of weighted out-degree centrality within competitive-elite teams

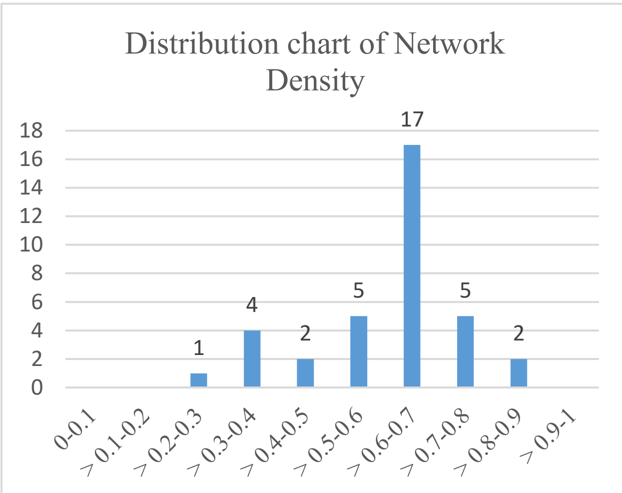

Figure 5.5. Frequency distribution chart of network density within competitive-elite teams

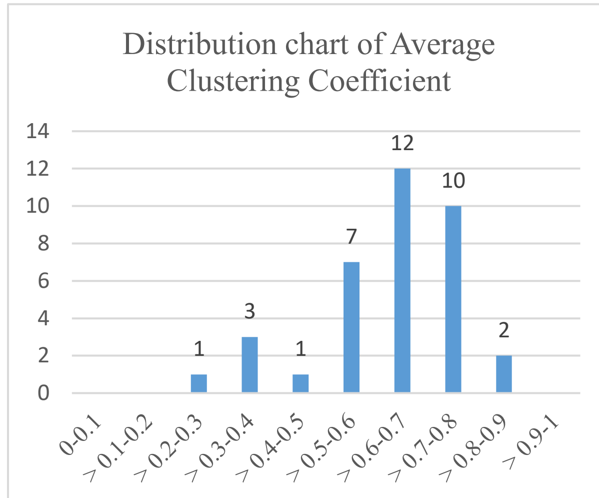

Figure 5.6. Frequency distribution chart of average clustering coefficient within competitive-elite teams

APPENDIX C

IRB APPROVAL MEMORANDUM

FLORIDA STATE UNIVERSITY

OFFICE *of the* VICE PRESIDENT *for* RESEARCH

APPROVAL

November 21, 2019

Dear Asaf Blatt:

On 11/20/2019, the IRB reviewed the following submission:

Type of Review:	Expedited (5) Data, documents, records, or specimens; (7)(a) Behavioral research
Title:	Team Coordination and Game-Based Interaction Networks in Soccer: analyzing team coordination properties of elite soccer teams based on intra-team passes patterns
Investigator:	Asaf Blatt
Submission ID:	STUDY00000724
Study ID:	STUDY00000724
Funding:	None
IND, IDE, or HDE:	None

Documents Reviewed:	• Asaf Blatt- Prospectus- Approved.pdf, Category: Protocol; • Barcelona - Real Madrid 5-1.pdf, Category: Other; • Team Coordination and Game-based Interaction Networks in Soccer/ Asaf Blatt, Category: IRB Protocol;

The IRB approved the protocol, effective from 11/20/2019.

You are advised that any modification(s) to the protocol for this project must be reviewed and approved by the IRB prior to implementation of the proposed modification(s). Federal regulations require that the Principal Investigator promptly report any new information related to this protocol (see Investigator Manual (HRP-103)).

In conducting this protocol, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system.

Sincerely,

Human Subjects Research Office humansubjects@fsu.edu

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BIOGRAPHICAL SKETCH

Asaf Blatt was born and raised in Tel-Aviv, Israel, with his parents Itzhak and Rachel, and his brothers, Amir and Tomer. Asaf was inspired to study psychology throughout a volunteering project with disabled children during high school. Following three years of military service in the Israeli Air Force, Asaf completed a Bachelor of Arts in psychology in 2014 and a Master of Arts in social psychology in 2016 from the Interdisciplinary Center (IDC) Herzliya in Israel. Asaf enrolled in the sport psychology doctoral program at Florida State University in the fall of 2016. Asaf is involved in a few entrepreneurial projects that integrate sport, exercise, psychology, and technology. He was the founder and the owner of "Tilt it," an innovative start-up intended for assisting children with coordination and balance difficulties. The start-up was chosen to represent Israel at Microsoft's worldwide conference on sensors in Redmond, WA. Asaf wishes to provide mental performance consulting services to various performers and professional sport teams, alongside conducting research and teaching in the field of sport and exercise psychology.