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Team Sports Performance Analysed through the Lens of Social Network Theory: Implications for Research and Practice

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Table of Contents

Figure captions

Fig. 1 Schematic representation of graph types: (a) digraph composed of a set of vertices (black circles) connected by directed edges (black arrows); (b) directed weighted graph in which edges (black lines) connect vertices (black circles) through associated weights.

Fig. 2 Representation of interpersonal interactions between teammates: (a) network of interpersonal interactions displayed in a 1-4-3-3 tactical formation, obtained from adjacency matrix processing in nodexl (social network software). Black circles represent players; blue arrows indicate pass direction. The origin of the arrow indicates the player who passed the ball and the arrowhead indicates the player who received the ball. The width and colour of each arrow represents the quantity or density of passes completed between players during performance (blue thicker arrows represent a greater quantity of passes between players), whereas circle size represents players who participate more frequently in attacking phases (bigger black circles represent players who receive and perform more passes); (b) adjacency matrix representing interpersonal interactions between teammates. *GK* goalkeeper, *CRD* central right defender, *CLD* central left defender, *LD* left defender, *RD* right defender, *DM* defensive midfielder, *LM* left midfielder, *RM* right midfielder, *LW* left wing, *RW* right wing, *FW* forward.

Abstract This paper discusses how social network analyses and graph theory can be implemented in team sports performance analyses to evaluate individual (micro) and collective (macro) performance data, and how to use this information for designing practice tasks. Moreover, we briefly outline possible limitations of social network studies and provide suggestions for future research. Instead of cataloguing discrete events or player actions, it has been argued that researchers need to consider the synergistic interpersonal processes emerging between teammates in competitive performance environments. Theoretical assumptions on team coordination prompted the emergence of innovative, theoretically-driven methods for assessing collective team sport behaviours. Here, we contribute to this theoretical and practical debate by conceptualising sports teams as complex social networks. From this perspective, players are viewed as network nodes, connected through relevant information variables (e.g., a ball passing action), sustaining complex patterns of interaction between teammates (e.g., a ball passing network). Specialized tools and metrics related to graph theory could be applied to evaluate structural and topological properties of interpersonal interactions of teammates, complementing more traditional analysis methods. This innovative methodology moves beyond use of common notation analysis methods, providing a richer understanding of the complexity of interpersonal interactions sustaining collective team sports performance. The proposed approach provides practical applications for coaches, performance analysts, practitioners and researchers by establishing social network analyses as a useful approach for capturing the emergent properties of interactions between players in sports teams.

Key Points

- The network approach highlights interactional processes established by team players within- and between-teams as a major focus of performance analysis.
- Conceptualization of sports teams as complex social networks provides novel insights regarding synergistic processes underlying the organization and function of teams in performance environments.
- Social network analysis could complement traditional performance analysis methods by analysing the complexity of dynamic patterns in interpersonal coordination tendencies emerging within and between teams at different levels of analysis.

1 Introduction

Investigating cooperative and competitive interaction tendencies between performers is a major theme in team sports performance analysis. Cooperation refers to the purposive contribution of individual efforts in achieving performance sub-goals [1]. High levels of cooperation allow collectives to increase their competitive performance. Biological characteristics of competition and cooperation are ubiquitous in nature, with groups of organisms tending to display both in many interactions. They are also present in human societies [2]. Sports teams are a microcosm of human societies: a group of individuals who develop cooperative interactions, bounded by specific spatial-temporal constraints, to achieve successful competitive performance outcomes [3]. Although composed of individual members, sports teams typically function as an integrated whole, displaying an intricate and complex set of behaviours impossible to predict at an individual level of analysis [3, 4]. These emergent patterns are not merely the sum of individual aggregated performances *per se* but arise through continuous interactions among group members [3].

Despite providing meaningful information about performance in some dimensions (e.g., technical), traditional notational analysis methods struggle to cope with the complex competitive and cooperative interactions emerging between individuals at different spatial and temporal scales [5, 6]. Beyond discrete indicators provided by traditional methods, team sports performance analysis needs to consider theoretical and practical frameworks that support evaluation of emergent structural and topological properties that underlie team functionality. Recent work has highlighted the value of re-conceptualizing research and practice in team sports performance analysis, proposing new investigative methods, more coherent with principles of dynamical systems and complexity sciences [7, 8, 9,10]. Additionally, a body of empirical studies has begun to analyse interpersonal interactions emerging within and between sport teams utilising social network analyses [11, 12, 13]. Like other collective social systems, sports teams can be conceptualized as complex social networks in which structural and topological properties of interpersonal interactions emerge between teammates and opponents under the ecological constraints of competitive performance environments. Here, we re-conceptualise sports teams as complex social networks, highlighting the applicability of graph theory for modelling social interactions in team sports performance. There are some potential advantages of considering concepts and tools of social network theory to evaluate the web of interpersonal interactions shaping collective team sports performance. Possible limitations are associated with these techniques and new insights offered by social network analyses can elucidate research on interpersonal interactions in team sports.

2 Sports teams as complex social networks

A social collective can be conceived as a network composed of individuals called nodes, connected by specific types of relational ties [14]. Like other complex social systems (e.g., organizations), team sports are composed of different system agents (e.g., players), interacting in various ways, revealing emergent and self-organizing behaviours during team coordination [15]. Emergence of coordinative behaviours in social networks is based on formation of interpersonal synergies between players [16]. Synergies or coordinative structures in an individual athlete have been defined as functional groupings of structural elements (e.g., neurons, joints, etc.), temporarily constrained to act as a single and coherent unit [17], enabling team members to act in collective sub-systems [18]. In competitive sport, teams can be characterized as a group of performers who interact in a dynamic, interdependent and adaptive way, managing efforts towards achieving common goals [19]. Teamwork can be interpreted as the functional behaviours emerging from performers within groups, resulting from coordination requirements imposed by interdependent tasks [20]. One example of such requirements was reported by Silva et al. [21] who verified that emergent synergies (entirely novel perception-action relations) established by teammates were formed and dissolved swiftly, resulting from locally-created information, specifying shared affordances for synergy formation. Shared affordances constitute collective environmental resources that exist independently of individuals who might learn to perceive and use them [22]. These shared affordances may constitute network opportunities for enhancing team coordination [22].

In performance, competing teams reveal specific structural and dynamical properties, pivotal for the organization and function of these complex social systems, discerned through analysis of collective behaviours. Behaviours of complex systems, (e.g., organizations/teams), emerge from the orchestrated local, pairwise interactions of system components [23]. This process foments the development and maintenance of system goals for teammates, operating together as a single unit. They need to continually seek, explore and establish effective ways of creating and maintaining the flow of interactional patterns, while coordinating decision-making and actions [24].

2.1 Social network analysis: An interdisciplinary perspective on collective performance in team sports

Social network research seeks to uncover patterns of behavioural interactions characterizing relations between actors (components of a social system), and to ascertain constraints that promote pattern formation [25]. Freeman [26] highlighted four properties of social network analysis: 1) importance of interactions between social actors; 2) significance of data collection and analysis sustained by social interactions; 3) revelation and display of interaction patterns through graphic imagery; and 4), description of interaction patterns of between system agents, using computational and mathematical modelling. Nodes or vertices represent individual actors within networks, in which ties (also called edges or links) represent types of interactions that bind actors [14, 27, 28]. This approach in team sports research raises pertinent questions, including: What differentiates this approach from others applied in team sports performance analyses? And, how can team sports performance analyses benefit from implementation of this approach? Social network analysis addresses the nature of interdependencies in team structures, where intra-group interactions are important for development and maintenance of collaborative behaviours, including aspects like cohesiveness, roles and hierarchies among players [29]. Network analysis investigates patterns of interactions from whole to part, from system structure to individual relations, and from behaviours to attitudes [14]. Network analysis bridges the gap between the *micro* (e.g., dyads, triads and small groups) and *macro* (e.g., the whole structure) levels of analysis [27]. Team sports environments are well suited for social network investigations, being composed of a number of well-defined elements. Competitive games contain clear rules and the strength of interaction patterns within and between teams, relative to performance, can be objectively assessed [11]. Support for social networks analysis requires elaboration of adjacency matrices (e.g., using simple spreadsheet tables), and manipulation of social network analysis software (e.g., nodexl), permitting representation, analysis, visualization or simulation of nodes (e.g., players) and edges (e.g., passes). These software packages provide mathematical and statistical routines that can elucidate graph properties.

Social network analysis research [11, 12, 13, 30, 31] has begun to reveal relational patterns (communication systems) emerging from interpersonal interactions in team sports. For example, a network approach, and application of its measures, has characterised cooperation between players in a football team during competitive performance [13, 32]. Other studies have reported a power law degree distribution (scale-free invariant) capturing emergence of passing behaviours [33]. Research has shown that game momentum can be represented by the number of triangles (triangular passing in groups of three players) attained in attacking sequences of play [33]. Other studies have confirmed the validity of network approaches to quantification of contributions by different individuals to overall team performance [34]. The impact of network structure on team performance has also been examined, showing that higher density levels, and low centralization of interactions, are associated with more successful performance outcomes [11].

Regardless, there is still a need for more performance analyses in team sports using a network approach, with a powerful theoretical framework that can sustain a network approach lacking. The elaboration of such a theoretical framework might heighten sport scientists' awareness of the main concepts and tools when studying individual and team performance. Extrapolation of this framework to coach education programs is also important to consider with practical interpretations reframed by relevant concepts like nodes, and edges. In addition to complementing other pedagogical tools in modelling social interactions, use of concepts and tools derived from graph theory needs to be clearly extrapolated to sports performance contexts, without compromising data interpretation. Here, we propose the adoption of a network approach in verifying the importance and complexity of social interactions in studies of team sports dynamics.

3 Graph theory as a tool for modelling and analysing social interactions in team sports

In team sports, functional performance is predicated on a complex network of social interactions established among teammates [35]. Many of its principles have emerged from graph theory, and social network analysis uses algorithms and procedures that map social structures within collectives [36]. Several disciplines have used graphs to model specific types of interactions and processes emerging in many complex systems, especially those with biological, physical, and social characteristics. A graph $G = (V, E)$ consists of a non-empty vertex set $V(G)$ and a finite family $E(G)$ of unordered pairs of elements of $V(G)$ called edges, such that, an edge $\{v, w\}$ joins the vertices v and w, being abbreviated to vw [37, 38].

Different types of graphs are exemplified in Figure 1. Weighted graphs have edges which contain associated weights, characterized by a real number [38]. Directed graphs or digraphs are composed of a set of vertices connected by edges which assign a direction from one vertex to another [38, 39].

*** insert Figure 1 here ***

Fig. 1 Schematic representation of types of graphs: (a) digraph composed of a set of vertices (black circles) connected by directed edges (black arrows); (b) directed weighted graph in which the edges (black lines) connect the vertices (black circles) through associated weights (number of times that vertices interact with each other).

In team sports, weighted graphs indicate the strength of interactions between teammates, for example, in passing behaviours or in rotating positions on field/on court. They also show directedness, since in team sports, players pass the ball in a specific direction from one player to another (Figure 2a). When recording graph information, computer scientists and mathematicians utilise the adjacency list, adjacency matrix and incidence matrix. The most commonly used tool to build graphs in team sports performance analysis is the adjacency matrix, which represents which vertices in a graph are adjacent to other vertices [40]. Previous studies have used adjacency matrices to characterize interpersonal interactions of teammates, in team sports like water polo [35] and football [41, 13, 32]. These matrices have been used to build a finite n x n network, where entries coded by number "1", represent ways that players interact (e.g., when *GK* passed the ball to *CRD*), and code number "0" represents those players who do not interact (Figure 2b).

*** insert Figure 2 here ***

Fig. 2 Representation of interpersonal interactions between teammates. (a) network of interpersonal interactions displayed in 1-4-3-3 tactical formation, obtained from adjacency matrix processing in nodexl (social network software). Black circles represent players and the blue arrows indicate pass direction. The origin of the arrow indicates the player who passed the ball and the arrowhead indicates the player who received the ball. The width and colour of each arrow represents the quantity or density of passes completed between players during performance (the blue thicker arrows represent a greater quantity of passes between players), whereas the size of circles represent players who participate more often in attacking phases (bigger black circles represent players who receive and perform more passes). (b) adjacency matrix representing interpersonal interactions between teammates. *GK* goalkeeper, *CRD* central right defender, *CLD* central left defender, *LD* left defender, *RD* right defender, *DM* defensive midfielder, *LM* left midfielder, *RM* right midfielder, *LW* left wing, *RW* right wing, *FW* forward.

4 Social network properties and collective team performance: A novel set of team sports performance indicators?

Increasing evidence on other collective social system (e.g., organizations) behaviours suggests that structural properties of networks (e.g., centrality) characterizing interactions of individuals within a collective, are related to performance, here regarded as a goal-oriented process of sharing information (non-material-verbal - or other, through implicit communication) [42, 43, 44, 45, 46]. Orchestration of behaviours within teams, and interpersonal interactions that bind teammates, are essential for team performance [11]. To achieve complex task goals, multi-agent systems (e.g., sports teams), should exhibit relational structures that privilege interdependency of behaviours and coordination to solve problems that emerge within competitive performance contexts and to achieve common performance goals [47]. Social network analysis provides information on their purpose and functionality through analysis of network structures [48].

Studies of team sports have demonstrated that the emergence of such network properties can be related to team performance (here regarded as a goal-oriented process of sharing information through material-passing the ball or other, through explicit communication) [34, 12, 11, 13], with others showing that team sports contain properties related to small-world [35] and scale-free networks [33]. The small-world concept infers that, despite their often large size, most networks have a relatively short path between any two nodes, with distance defined as the number of edges along the shortest path connecting them [49]. Scale-free networks have a distribution with a power-law tail. The fraction $P(k)$ of nodes in the network has connections to other nodes with large values of k as $P(k) \sim k^{-y}$ [50]. There are several network properties that can elucidate the structure and function of complex systems, helping sport scientists to characterize the continuous interactions of teammates in sports teams.

For instance, a characteristic path length measures the separation between two vertices (e.g., players in team games) in a graph (global property). A clustering coefficient measures the cliquishness of a network neighbourhood (local property) [49]. Characteristic path length can reveal how many passes are needed for the ball to traverse from one particular player to another. Clustering coefficients provide coaches and performance analysts with knowledge about subgroups of players who coordinate their actions more frequently [51]. This idea is exemplified in football when two players coordinate their actions with each other more frequently than with other teammates, forming a cluster. Globally, high values of a clustering coefficient might indicate a team disposition to form functional clusters [51], with players tending to create tightly knit groups comprising high density ties. Graph theory provides four measures of centrality which indicate the importance of a vertex (e.g., a team player) in a graph, including, degree, 'betweenness', closeness and eigenvector centrality [52, 53]. Degree centrality consists of the number of ties incident upon a node [54]. Since in team sports, players pass the ball in a specific direction from one player to another, the degree of a vertex can be defined according to two types of centrality: 'indegree' (number of passes directed to the player) and 'outdegree' (number of passes that the player directs to others). These metrics move beyond simplistic frequency counts of passes made, providing insights on how many passes each player receives and how often he/she passes the ball effectively. Betweenness centrality is defined as the number of times that a vertex connects two other vertices through their shortest paths [52, 53, 54]. These data provide insights on the amount of network 'flow' that a given player "controls" (e.g., player(s) responsible for connecting the defensive sector within a midfield area in football). Closeness centrality of a vertex is defined as the sum of distances from all other vertices presented in a graph, with this distance defined as the length of the shortest paths from one vertex to another [52, 53, 54]. This network metric provides information on adjacency of one player to others, where players with low closeness scores are adjacent to others, providing conditions for receiving flows (e.g., receive a pass or rotate with the nearest player) more rapidly. Eigenvector centrality measures the influence of a vertex in a graph [54]. Density and centralization consists of two network structural properties characterizing global interaction patterns of a team. Density describes the overall level of cooperation/coordination between teammates, whereas centralization reflects the extent to which interactions are unequally distributed among team members [45]. Analysis of these data can inform coaches and performance analysts about: (i) the functionality of team organization where all players interact with similar proportionality, and (ii), whether team organization relies on a heterogeneous system level, characterized by unequal proportionality of interactions, depending on the input of specific "key players". With this information, coaches can manipulate different practice task constraints to facilitate emergence of specific team dynamics. For example, team dynamics could emerge from implementing a conditioned activity involving prominent players, facilitating self-organization tendencies in a team. Or team dynamics could be manipulated to promote/inhibit emergence of influence of different player subgroups during competition. Regardless, researchers may face some problems when applying such techniques, with four limitations reported in social network studies: 1) the majority of studies employing social network analysis have observed information exchange between players mainly through passing behaviours; 2) the variability of player's performance outcomes, associated with specific match events (e.g., match location) is in most cases disregarded; 3) over-emphasis on network attacking behaviours, thus not considering the influence of defensive behaviours on network functionality and adaptability; 4) most of the metrics used to model social interactions are based on paths, which can be inappropriate for sports contexts. Undoubtedly in team sports (e.g., football), information flows between players beyond passing behaviours, with the pass being only one essential technical action (e.g., dribble) that players perform. Variability of player performance should also be carefully evaluated since his/her performance may be affected by several factors (e.g., fatigue), throughout the game. Most studies analyse results according to the total number of interactions displayed by the adjacency matrix, which does not reflect the inherent dynamics of team games. The adoption of dynamic network analysis [33] can reveal more accurate and relevant information about the dynamics of individual and team performance. It is crucial for further investigations to conduct analyses of team defensive behaviours, providing pivotal information on team functionality and adaptability. Here, both teams are connected through a feedback loop (competition), where the behaviours of a given network A will be regarded as external input by network B, and vice-versa, influencing its global topology and local dynamics [33]. Finally, the use of geodesic paths as a tool to model social interactions can exert a negative impact on interpretation of results, since the use of paths suggests that whatever flows through the network only moves along the shortest possible paths [54]. This may not be appropriate when applied to sporting contexts, since for example, in football, players do not necessarily pass the ball uniquely to a player with the shortest path. Thus, the more appropriate is to use walks instead of paths, since walks model interactions assuming that trajectories can not only be circuitous, but also revisit nodes and lines multiple times along the way [54]. A key next step is to develop relevant analytical solutions (e.g., formulas) for analysing specific topological structures of team sports, or seek metrics that use walks to model interactions.

5 Conclusions and practical implications

We highlighted how sports teams can be conceptualized as complex social networks composed of different individuals, who develop and adapt cooperative and coordinative relations to achieve common performance goals.

When evaluating collective performance in training or competition, the adoption of social network analyses, not replacing, but complementing, other pedagogical methods, can provide novel insights on the complexity of interpersonal interactions that shape team behaviours. Such information may be utilised by coaches and/or performance analysts for designing practice learning environments. These techniques furnish an adequate approach for team sports performance analysis, consistent with the assumptions of complexity sciences and dynamical systems theory, capturing the emergent properties presented in the interactions of players in sports teams.

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Compliance with Ethical Standards

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