

Team sports performance analysed through the lens of social network theory: implications for research and practice

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

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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.

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

19 **Key Points**

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

28

1 **1 Introduction**

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

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

1 sports performance. Possible limitations are associated with these techniques and new insights offered by
2 social network analyses can elucidate research on interpersonal interactions in team sports.

3 **2 Sports teams as complex social networks**

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

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

28 *2.1 Social network analysis: An interdisciplinary perspective on collective performance in team sports*

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

24 Social network analysis research [11, 12, 13, 30, 31] has begun to reveal relational patterns
25 (communication systems) emerging from interpersonal interactions in team sports. For example, a
26 network approach, and application of its measures, has characterised cooperation between players in a
27 football team during competitive performance [13, 32]. Other studies have reported a power law degree
28 distribution (scale-free invariant) capturing emergence of passing behaviours [33]. Research has shown
29 that game momentum can be represented by the number of triangles (triangular passing in groups of three
30 players) attained in attacking sequences of play [33]. Other studies have confirmed the validity of

1 network approaches to quantification of contributions by different individuals to overall team
2 performance [34]. The impact of network structure on team performance has also been examined,
3 showing that higher density levels, and low centralization of interactions, are associated with more
4 successful performance outcomes [11].

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

15 **3 Graph theory as a tool for modelling and analysing social interactions in team sports**

16 In team sports, functional performance is predicated on a complex network of social interactions
17 established among teammates [35]. Many of its principles have emerged from graph theory, and social
18 network analysis uses algorithms and procedures that map social structures within collectives [36].
19 Several disciplines have used graphs to model specific types of interactions and processes emerging in
20 many complex systems, especially those with biological, physical, and social characteristics. A graph $G =$
21 (V, E) consists of a non-empty vertex set $V(G)$ and a finite family $E(G)$ of unordered pairs of elements of
22 $V(G)$ called edges, such that, an edge $\{v, w\}$ joins the vertices v and w , being abbreviated to vw [37, 38].

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

26

27 *** insert Figure 1 here ***

1

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

6 In team sports, weighted graphs indicate the strength of interactions between teammates, for example, in
7 passing behaviours or in rotating positions on field/on court. They also show directedness, since in team
8 sports, players pass the ball in a specific direction from one player to another (Figure 2a). When recording
9 graph information, computer scientists and mathematicians utilise the adjacency list, adjacency matrix
10 and incidence matrix. The most commonly used tool to build graphs in team sports performance analysis
11 is the adjacency matrix, which represents which vertices in a graph are adjacent to other vertices [40].
12 Previous studies have used adjacency matrices to characterize interpersonal interactions of teammates, in
13 team sports like water polo [35] and football [41, 13, 32]. These matrices have been used to build a finite
14 $n \times n$ network, where entries coded by number “1”, represent ways that players interact (e.g., when *GK*
15 passed the ball to *CRD*), and code number “0” represents those players who do not interact (Figure 2b).

16

17 *** insert Figure 2 here ***

18

19 **Fig. 2** Representation of interpersonal interactions between teammates. (a) network of interpersonal
20 interactions displayed in 1-4-3-3 tactical formation, obtained from adjacency matrix processing in nodexl
21 (social network software). Black circles represent players and the blue arrows indicate pass direction. The
22 origin of the arrow indicates the player who passed the ball and the arrowhead indicates the player who
23 received the ball. The width and colour of each arrow represents the quantity or density of passes
24 completed between players during performance (the blue thicker arrows represent a greater quantity of
25 passes between players), whereas the size of circles represent players who participate more often in
26 attacking phases (bigger black circles represent players who receive and perform more passes). (b)
27 adjacency matrix representing interpersonal interactions between teammates. *GK* goalkeeper, *CRD*

1 central right defender, *CLD* central left defender, *LD* left defender, *RD* right defender, *DM* defensive
2 midfielder, *LM* left midfielder, *RM* right midfielder, *LW* left wing, *RW* right wing, *FW* forward.

3

4 **4 Social network properties and collective team performance: A novel set of team sports** 5 **performance indicators?**

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

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

26 For instance, a characteristic path length measures the separation between two vertices (e.g., players in
27 team games) in a graph (global property). A clustering coefficient measures the cliquishness of a network
28 neighbourhood (local property) [49]. Characteristic path length can reveal how many passes are needed

1 for the ball to traverse from one particular player to another. Clustering coefficients provide coaches and
2 performance analysts with knowledge about subgroups of players who coordinate their actions more
3 frequently [51]. This idea is exemplified in football when two players coordinate their actions with each
4 other more frequently than with other teammates, forming a cluster. Globally, high values of a clustering
5 coefficient might indicate a team disposition to form functional clusters [51], with players tending to
6 create tightly knit groups comprising high density ties. Graph theory provides four measures of centrality
7 which indicate the importance of a vertex (e.g., a team player) in a graph, including, degree,
8 'betweenness', closeness and eigenvector centrality [52, 53]. Degree centrality consists of the number of
9 ties incident upon a node [54]. Since in team sports, players pass the ball in a specific direction from one
10 player to another, the degree of a vertex can be defined according to two types of centrality: 'indegree'
11 (number of passes directed to the player) and 'outdegree' (number of passes that the player directs to
12 others). These metrics move beyond simplistic frequency counts of passes made, providing insights on
13 how many passes each player receives and how often he/she passes the ball effectively. Betweenness
14 centrality is defined as the number of times that a vertex connects two other vertices through their shortest
15 paths [52, 53, 54]. These data provide insights on the amount of network 'flow' that a given player
16 "controls" (e.g., player(s) responsible for connecting the defensive sector within a midfield area in
17 football). Closeness centrality of a vertex is defined as the sum of distances from all other vertices
18 presented in a graph, with this distance defined as the length of the shortest paths from one vertex to
19 another [52, 53, 54]. This network metric provides information on adjacency of one player to others,
20 where players with low closeness scores are adjacent to others, providing conditions for receiving flows
21 (e.g., receive a pass or rotate with the nearest player) more rapidly. Eigenvector centrality measures the
22 influence of a vertex in a graph [54]. Density and centralization consists of two network structural
23 properties characterizing global interaction patterns of a team. Density describes the overall level of
24 cooperation/coordination between teammates, whereas centralization reflects the extent to which
25 interactions are unequally distributed among team members [45]. Analysis of these data can inform
26 coaches and performance analysts about: (i) the functionality of team organization where all players
27 interact with similar proportionality, and (ii), whether team organization relies on a heterogeneous system
28 level, characterized by unequal proportionality of interactions, depending on the input of specific "key
29 players". With this information, coaches can manipulate different practice task constraints to facilitate
30 emergence of specific team dynamics. For example, team dynamics could emerge from implementing a

1 conditioned activity involving prominent players, facilitating self-organization tendencies in a team. Or
2 team dynamics could be manipulated to promote/inhibit emergence of influence of different player
3 subgroups during competition. Regardless, researchers may face some problems when applying such
4 techniques, with four limitations reported in social network studies: 1) the majority of studies employing
5 social network analysis have observed information exchange between players mainly through passing
6 behaviours; 2) the variability of player's performance outcomes, associated with specific match events
7 (e.g., match location) is in most cases disregarded; 3) over-emphasis on network attacking behaviours,
8 thus not considering the influence of defensive behaviours on network functionality and adaptability; 4)
9 most of the metrics used to model social interactions are based on paths, which can be inappropriate for
10 sports contexts. Undoubtedly in team sports (e.g., football), information flows between players beyond
11 passing behaviours, with the pass being only one essential technical action (e.g., dribble) that players
12 perform. Variability of player performance should also be carefully evaluated since his/her performance
13 may be affected by several factors (e.g., fatigue), throughout the game. Most studies analyse results
14 according to the total number of interactions displayed by the adjacency matrix, which does not reflect the
15 inherent dynamics of team games. The adoption of dynamic network analysis [33] can reveal more
16 accurate and relevant information about the dynamics of individual and team performance. It is crucial for
17 further investigations to conduct analyses of team defensive behaviours, providing pivotal information on
18 team functionality and adaptability. Here, both teams are connected through a feedback loop
19 (competition), where the behaviours of a given network A will be regarded as external input by network
20 B, and vice-versa, influencing its global topology and local dynamics [33]. Finally, the use of geodesic
21 paths as a tool to model social interactions can exert a negative impact on interpretation of results, since
22 the use of paths suggests that whatever flows through the network only moves along the shortest possible
23 paths [54]. This may not be appropriate when applied to sporting contexts, since for example, in football,
24 players do not necessarily pass the ball uniquely to a player with the shortest path. Thus, the more
25 appropriate is to use walks instead of paths, since walks model interactions assuming that trajectories can
26 not only be circuitous, but also revisit nodes and lines multiple times along the way [54]. A key next step
27 is to develop relevant analytical solutions (e.g., formulas) for analysing specific topological structures of
28 team sports, or seek metrics that use walks to model interactions.

29 **5 Conclusions and practical implications**

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

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

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18

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