

The Role of Hypernetworks as a Multilevel Methodology for Modelling and Understanding Dynamics of Team Sports Performance.

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Figure captions

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3 **Fig. 1** Example of a multilevel hypernetwork representation (from bottom to top): All players are tagged
4 by numbers: Those of the black team play from left to right: Players from the blue team play from right to
5 left. Goalkeepers are attached to their respective goals and the simplices' formation is based on players'
6 proximity on field with the arrows depicting their direction of displacement. Level N is the simplest and
7 represents player location on field (black team is organised according to a 1-4-3-3 configuration (one
8 goalkeeper, four defenders, three midfielders and three forwards) and the blue team in a 1-4-4-2
9 configuration (one goalkeeper, four defenders, four midfielders and two forwards)). Level N + 1 depicts
10 two consecutive time frames of the match (from left to right) and refers to proximity-based simplex
11 interactions, which are foundations for defining the simplex sets identified for the two time frames.
12 Level N + 2 represents emerging microstructures of play showing both numerical imbalance (3vs.2) and
13 numerical balance (1vs.1), with respect to field location (LC – left corridor; CC – central corridor; RC –
14 right corridor). Level N + 3 represents the dynamic interaction between simplices, here exemplified by
15 the interaction between players that form the simplex of the defensive line sector with players that form
16 the simplex of the midfield line sector of the blue team, without resorting to geographical proximity
17 criteria.

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20 **Fig. 2** Schematic representation of players' simplices and the ball line (black dashed line). Players
21 composing the black team play from left to right, while players from the blue team play from right to left.
22 Simplices formation is based on geographical proximity between players with goalkeepers being attached
23 to their goals. The player tagged with number 24 has the ball (B) and is involved in a simplex of 2vs.2
24 along with player 23 from the black team, and players 9 and 13 from the blue team. Behind the ball line
25 are located the goalkeeper (29), and two types of simplices (1vs.1 composed by players 26 and 6; 2vs.1
26 composed by players 18 and 28 from the black team and player 3 from the blue team). Ahead of the ball
27 line are located three types of simplices (1vs.1 composed by players 16 and 5; 3vs.2 with players 15, 2, 12
28 from the blue team and players 19 and 27 from the black team; 2vs.2 composed by players 22 and 17
29 from the black team and players 8 and 11 from the blue team), and the goalkeeper from the blue team
30 coded by number 14.

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1 **Abstract** Despite its importance in many academic fields, traditional scientific methodologies struggle to
2 cope with analysis of interactions in many complex adaptive systems, including sports teams. Inherent
3 features of such systems (e.g., emergent behaviours) require a more holistic approach to measurement and
4 analysis for understanding system properties. Complexity sciences encompass a holistic approach to
5 research on collective adaptive systems, which integrates concepts and tools from other theories and
6 methods (e.g., ecological dynamics and social network analysis) to explain functioning of such systems in
7 natural performance environments. Multilevel networks, such as hypernetworks, comprise novel and
8 potent methodological tools for assessing team dynamics at more sophisticated levels of analysis,
9 increasing their potential to impact on understanding of competitive performance. Here, we discuss the
10 potential of concepts and tools derived from studies of multilevel networks for revealing key properties of
11 sports teams as complex, adaptive social systems. This type of analysis can provide valuable information
12 on team performance, which can be used by coaches, sport scientists and performance analysts for
13 enhancing practice and training. We examine the relevance of network sciences, as a sub-discipline of
14 complexity sciences, for studying dynamics of relational structures in sports teams during practice and
15 competition. We explore benefits of implementing multilevel networks, in contrast to traditional network
16 techniques, highlighting future research opportunities. We conclude by recommending methods for
17 enhancing applicability of hypernetworks in analysing collective dynamics at multiple levels.

18

19 **Key Points:**

- 20 • Inherent properties of complex social systems require more holistic methodological approaches
21 for studying adaptive system functioning.
- 22 • Complexity sciences provide a holistic and comprehensive approach for understanding
23 continuous interactions that emerge between individual competing athletes to explain team
24 dynamics.
- 25 • Use of multilevel networks such as hypernetworks, circumscribed in the complexity sciences
26 paradigm, has the potential to overcome major limitations that exist in traditional network
27 analyses, enabling a more sophisticated and accurate method of understanding relational
28 structures underlying team functioning at multiple levels.

29

1 **1 Introduction**

2 Traditionally, team interactions in sports performance contexts have been conceived as the aggregation of
3 individual performances. Typically, in an attempt to identify relevant properties of such collective
4 systems, sports scientists have applied a set of methodological tools that recursively decompose the parts
5 of the system into individual units. Once gaining insights into how individual units (players) behave
6 within the system, sport practitioners recombine them again into a collective/whole system. Such a
7 reductionist approach is based on linear thinking and models, consonant with analysis of reducible, linear
8 systems, whose behaviour is commonly depicted as resulting from the aggregate of individual actions
9 within the system [1]. This line of thinking is aligned with simple models of information processing,
10 resulting from linear input-transformation-output processes [2]. However, what happens when such
11 systems display dynamic, complex, non-linear, interdependent behaviours? Indeed, traditional science has
12 been challenged to describe and explain how novel coordination patterns spontaneously emerge within
13 complex adaptive systems, such as schools of fish, colonies of insects and sports teams [3]. Despite being
14 composed of individual members, sports teams operate as an integrated whole, producing an intertwined
15 and complex set of behaviours that are not entirely predictable at an individual level of analysis [4, 5].
16 Such behavioural patterns are emergent and not merely an accumulation of individual performances per
17 se; instead, they arise from continuous, ongoing interactions amongst group members [6, 4]. Contrary to
18 postulates of linear models, complexity sciences have emerged as a holistic approach to understanding
19 behaviours of complex adaptive systems. Within the field of network sciences, an emergent
20 methodological approach is hypernetworks [7] that investigate group dynamics at *multiple levels* of
21 analysis [8]. In this position paper, we outline the benefits of utilising a multilevel approach, in contrast to
22 traditional network techniques, in analysing team dynamics during practice and competitive performance.
23 We start by briefly reviewing the importance of complexity sciences for studying complex social systems
24 in the realm of team sports performance. Next, we discuss the relevance of social network analysis (SNA)
25 (a sub-discipline utilised by complexity sciences) as a suitable framework for ascertaining the relational
26 structures exhibited by interactions between agents in sports teams during competition. We discuss the
27 adoption of multilevel networks, in contrast to traditional network techniques, as novel and potent
28 methodological tools for overcoming some of the limitations encountered in previous analysis of social
29 networks. Finally, we propose future research possibilities and methodological alternatives for enhancing
30 the multilevel approach.

1

2 **2 Complexity sciences: A multidisciplinary approach for studying social interactions in team sports**

3 A major question considered here is: Are theories and methods in complexity sciences relevant for
4 describing and analysing collective phenomena in sports? Complexity sciences have already
5 demonstrated, over past years [e.g., 9-13], effective methods for analysing behaviours of non-linear
6 systems. An important point to note is that, the more complex a system is (i.e. having *many interacting*
7 parts), the less amenable to linear, reductionist analyses it becomes. Previous studies have revealed that
8 the complexity sciences can provide profound insights on sports-related phenomena which are inherently
9 complex and multidimensional by nature.

10 Complexity sciences investigations of behaviours in complex adaptive systems have revealed
11 many *interacting* elements, whose behaviour is difficult to ascertain due to continuous interactions and
12 interdependencies between system components, and co-relations with their surrounding environments.
13 The delimitations of such open systems tend to be based on operational definitions (e.g., skin as a barrier
14 between organism and environment), which is not theoretically driven. Such systems display properties
15 underpinning integrated behaviours, significantly differing from properties and behaviours of their
16 individual elements. A fundamental property of complex systems is emergence. Emergent behaviours
17 cannot be simply irreducible to the behaviours of system elements. Rather, behaviour must be
18 contextualised according to how the elements interact within the system and environment within which
19 they are embedded. Moreover, self-organisation, adaptive behaviours, variability, nonlinearity, and
20 complex networking, constitute other key properties of such systems [14, 6].

21 The key challenges when analysing behaviours of such systems are related to their formal
22 modelling and simulation. Current research on team sports performance analysis has witnessed a
23 progressive increase on investigations of performance behaviours based on positional data (see, for
24 example, Agras et al. [15] and Sarmento et al. [16] for detailed reviews). Applications of novel and
25 sophisticated techniques, using non-linear statistical tools have supported capture of collective
26 behaviours, identified by variables such as team centroids (geometric centre of a group of players) and
27 team dispersion (how far players are apart), as well as team communication (e.g., networks underpinning
28 ball-passing sequences) and sequential patterns (predicting future passing sequences) [16]. Lately, there
29 has been increasing interest in research on team communication networks [e.g., 17-19].

1 Sports teams are composed of players interacting through several communicational channels, revealing
2 specific relational ties (e.g., through ball-passing actions). These interactions can be depicted by a
3 complex network with players representing the nodes of the network, and the links reflecting their
4 interactions on field [18, 20-22]. Network approaches are extremely useful, since application of their
5 concepts and methods can illuminate dynamical properties in individual and team sports [23-26],
6 contributing to a specialised body of knowledge for understanding the functioning of such complex
7 adaptive social systems.**3 Social network analysis (SNA) as a paradigm for modelling complex social**
8 **systems**

9 Theories and methods underpinning SNA include, for example, graph theory (mathematical
10 structures utilised for modelling pairwise relations between objects) and social structure analysis
11 pertaining to the field of sociology. Lately, SNA has extensively focused on sports performance data [18,
12 20, 27-30] as a means of analysing complex relational/structural interactions. The applicability of such an
13 approach is predicated on insights regarding interactions of structures that ultimately lead to emergent
14 complex phenomena [21, 31]. Indeed, re-conceptualisation of sports teams as complex social networks
15 [22, 32] has revealed novel research opportunities for researchers, sports scientists and performance
16 analysts to investigate the structural properties of teams during practice and competition linked to
17 successful performance outcomes.

18 Beyond the unique terminology (e.g., nodes/vertices, links/edges) used for modelling social
19 interactions within collectives, such an approach utilises specific conceptual and methodological tools for
20 understanding and predicting team performance. Despite being a promising methodological approach,
21 more coherent with the principles of complexity sciences in analysing complex social systems, traditional
22 network techniques contain specific limitations that may eventually hinder or even conceal important
23 information regarding team functioning during competition. Such limitations have been carefully
24 scrutinised in the works of Ribeiro et al. [22] and Ramos et al. [32], and researchers have proposed
25 possible alternatives and/or methodological tools that can ultimately reinforce the network approach for
26 adequately analysing the relational properties of sports teams.

27 **4 Hypernetworks as innovative and potent methodological tools for analysing dynamic relational**
28 **structures of sports teams**

29

1 Hypernetworks have recently emerged as a major hot topic of research for many branches of
2 science, including sports science. Multilevel analysis and representing relations via hypernetworks were
3 originally introduced by Johnson and Iravani [7] for analysing the dynamics of complex systems of robot
4 football agents. More recently, such an approach was extrapolated to investigate the dynamics of human
5 football players during competition [8]. Indeed, Johnson and Iravani [7] have proposed that a multilevel
6 approach can be extended to analyses of other multiagent systems (e.g., football teams) where dynamics
7 emerge from interactions between the agents. Research on hypernetworks is still fresh and much work is
8 needed to continue development of multilevel analytics. Its potential is enormous since it can override
9 most of the limitations found in traditional network techniques.

10 For example, a major limitation of traditional methods is that they only focus on binary relations
11 between two players [33]. Potentially, multilevel hypernetworks are not restricted to analysis of dyadic
12 relations; rather they support representation of simultaneous n -ary relations ($n > 2$) among sets of
13 nodes/vertices (i.e., team players). Their properties are represented by a hyperedge supporting
14 connections between more than two players (within and between teams) at the same time (called simplex,
15 plural - simplices) [33-37]. Hyperedges shed light on physical links (e.g., notation of who passes the ball
16 to whom) established between players which facilitate information exchanges. Also informational links
17 (e.g., values of interpersonal distances, velocity and acceleration) bound players' interactions. This is
18 particularly important because, for instance, researchers can analyse emergent interactions (by verifying
19 changes in the velocity and direction of each player's vectors) that led to the assembly and/or dissolution
20 of a specific simplex structure (e.g., to balance and/or unbalance the simplex). These interactions are
21 important because previous research (e.g. Ramos et al. [8]) has suggested that changes in velocity near the
22 goal allowed players to improve their positioning to score goals and/or to unbalance opposition defensive
23 structures.

24 Ramos et al. [8] confirmed the relevance of hypernetworks for extracting important information
25 from game performance data. Their data verified: i) the most frequently occurring simplices
26 configurations during the match; ii) dynamics of simplices' transformations (variations of players' speed
27 and direction) near the goal that led to the creation of goal-scoring opportunities, and: iii), dynamics of
28 interactions at higher complexity levels, i.e., interactions between simplices of simplices.

1 Next, we provide a detailed analysis of the conceptual and methodological implications of
2 applying multilevel hypernetworks in sport, addressing the main limitations of traditional network
3 techniques, as discussed in the article by Ribeiro et al. [22].

4 **5 Application of multilevel hypernetworks to understanding sport performance**

5

6 *5.1 The majority of studies employing social network analysis have observed information exchange*
7 *between players mainly through passing behaviours*

8

9 Hypernetworks can include an element R that describes relationships emerging within the set
10 (simplex) [36] composed by a given number of players in a sports team. Each simplex can be represented
11 by a convex hull computation (the minimum convex area containing all players in the simplex) and
12 includes the velocity of each player (vector velocity regarding the instant $t-1$ and t), as well as the velocity
13 of the geometric centre of the simplices. The simplices can be completed with information describing
14 other types of technical actions (e.g., ball manipulation (BM)) undertaken by players during performance.
15 Additionally, a computer procedure for calculating the simplices' hyperedges, defined with a proximity
16 criterion, can be implemented using GNU Octave and applied to each time frame of the match. Such a
17 proximity criterion implies that interactions between players, as well as sets of these interactions
18 (simplices), are assessed based on interpersonal distance values, especially spatial proximity and instant
19 speed relational variables [8]. This signifies that each player is connected to his/her nearest player (or
20 goal, for goalkeepers), while the same is verified at higher levels, where simplices can be linked to their
21 closest simplices [8].

22 To exemplify (Fig. 1), imagine a first simplex identified by σ_1 and represented by the following
23 set $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}\}$, where a_{16} , a_{23} , and a_{24} represent three attacking players, while d_9 and d_{13}
24 represent defending players. The simplex set can be enhanced by an element R_1 [8] which, basically,
25 identifies the relationships (microstructures of play) within the set $R_1=(3vs.2)$. The second simplex σ_2
26 represents the following set $\sigma_2 \{a_{16}, a_{24}, d_9\}$ identified by $R_2=(2vs.1)$, composed of two attackers and one
27 defender. Finally, the third simplex σ_3 is represented by $\sigma_3 \{a_{23}, d_{13}\}$ identified by $R_3=(1vs.1)$, composed
28 of one attacker and one defender. Hence, the respective microstructures of play are $R_1=(3vs.2)$, $R_2=(2vs.1)$
29 and $R_3=(1vs.1)$, and the corresponding simplices are $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3vs.2)\}$, $\sigma_2 \{a_{16}, a_{24}, d_9;$
30 $(2vs.1)\}$ and $\sigma_3 \{a_{23}, d_{13}; (1vs.1)\}$. Let us say that these simplices' transformation (from σ_1 to σ_3) was

1 observed during two consecutive time frames (t_1 - t_2) of the match in an attacking sequence that resulted in
2 a goal-scoring opportunity. Now, let us suppose that the configuration of the simplices' transformation
3 from σ_1 to σ_3 was provoked by a movement of player a_{23} from simplex σ_1 which ran with the ball at speed
4 (BM) further away from simplex σ_1 . This action performed by player a_{23} allowed him to dissociate along
5 with d_{13} (geographical proximity criteria) from previous simplex σ_1 , thus originating the formation of
6 simplices σ_2 and σ_3 .

7 We can add BM ($BM_{a_{23}-d_{13}}$) to $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3vs.2); BM_{a_{23}-d_{13}}\}$ as an extra layer to
8 complete the description of the set. Hence, the sequence of the following sets of simplices is: $\sigma_1 \{a_{16}, a_{23},$
9 $a_{24}, d_9, d_{13}; (3vs.2); BM_{a_{23}-d_{13}}\} \rightarrow \sigma_2 \{a_{16}, a_{24}, d_9; (2vs.1)\} + \sigma_3 \{a_{23}, d_{13}; (1vs.1)\}$. This example provides a
10 more complete description of the behaviours of both teams and how they evolve over time, which now
11 includes relevant information on other technical actions realized by the players. These actions might be
12 crucial for destabilising the numerical balance/imbalance of a given simplex, without focusing solely on
13 ball-passing events.

14 However, beyond providing qualitative information regarding team performance, other relevant
15 information can be included to quantitatively express relational dynamics of competing teams. This could
16 be exemplified by counting the number and types of microstructures of play (e.g., sub phases such as
17 1vs.1) emerging during practice [8], and also the frequency of other technical actions performed by
18 players during competition. The conceptualisation of team sports performance with a hypernetworks
19 methodology might help sports scientists and researchers develop novel performance metrics [8], capable
20 of capturing team synergies emerging between players. By using positional coordinates of players from
21 both teams and the ball, we can analyse, for example, how players pertaining to a specific simplex (the
22 defensive line sector) synchronise their movements with other players pertaining to another simplex (the
23 midfield line sector). This can be done, for example, by computing the mean relative phase of each player
24 to his/her corresponding simplices with which players interact throughout the match. Or, we may
25 ascertain how far both simplices (the defensive and midfield line sectors) are separated from each other
26 (e.g., through measurement of the simplices' geometric centre), providing insights into team compactness
27 and/or spread. Here, hypernetworks support the provision of detailed information on the players
28 composing each simplex and how synchronised or far/near simplices are.

29

1 5.2 Variability of player performance outcomes is associated with specific events in competitive
2 performance

3

4 Ribeiro et al. [22] highlighted the over-emphasis on frequency counts of actions in performance
5 analysis, suggesting that “Most studies analyse results according to the total number of interactions
6 displayed by the adjacency matrix, which does not reflect the inherent dynamics of team games” (pp.
7 1694). Implementation of multilevel hypernetworks can consider both space and time in analysis of team
8 dynamics since, for example, it can use geographical proximity criteria (if previously defined for creating
9 the simplices’ sets of nodes) and capture temporal changes by considering players’ geographical positions
10 over time (t_1, t_2, \dots, t_n) [8]. Furthermore, Johnson [35] introduced the concepts of *backcloth* and *traffic* to
11 emphasise the study of dynamics in multilevel analysis. The network is the backcloth involving fewer
12 dynamic structures, while the traffic relates to the network flows, thus considering higher rates of change
13 emerging within the backcloth [35]. Application of these novel ideas to team sports performance analysis,
14 might consider, for example, the disposition of players on field in football. Pplayers organised according
15 to positions in a 1-4-3-3 formation with one goalkeeper, four defenders, three midfielders and three
16 forwards, for example), with typical adjustments, can be the *backcloth*, and player displacements on field
17 (both off- an on-the-ball) is the *traffic*. Hence, each pre-defined team disposition on field may afford the
18 emergence of certain relational dynamics specific to that configuration. Playing in a configuration of 1-4-
19 3-3 is not the same as playing in a 1-4-4-2 configuration. Relational dynamics of players in both systems
20 may differ significantly. For example, the first configuration has only three midfielders and one central
21 forward, the latter has four midfielders and two forwards. These and other team properties might
22 constrain team dynamics, and thus promote specific individual and team behaviours.

23 Developing mathematical formalisms underlying the hypernetworks approach enables the
24 representation of a multilevel model for describing team behaviour dynamics, where micro-to-meso-to-
25 macro levels of relational structures are considered in a holistic analysis [8, 38], allowing us to investigate
26 higher complexity levels inherent to team sports competition (Fig. 1).

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Please insert Figure 1 near here

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5.3 Research over-emphasises analysis of attacking behaviours in performance analysis, rather than defensive behaviours

A major advance, compared to traditional network analysis, is that use of simplices can capture interactions of sets of players that may involve an arbitrary number of teammates and opponents [8]. Such an advance signifies permits analysis of both cooperative and competitive interactions emerging between players simultaneously. This approach ensures that both attacking and defending patterns of coordination are considered in analysis of team dynamics, providing insights regarding team functionality and adaptability during competitive performance. Adding information about ball location (e.g., position coordinates acquired through match analysis statistical reports, such as Opta Sports (London, United Kingdom) can furnish novel and rich insights regarding functional dynamics of both attacking and defending teams. Arguably, ball location onfield constitutes a major constraint which continually shapes how players from both teams continuously co-adapt their positioning on field. This could affect individual and team dynamics, which should be addressed in future investigations of hypernetworks. For example, by including information from ball location in hypernetworks analysis (Fig. 2) researchers are able to identify the player with the ball (*B*) in a given simplex n ($\sigma_n \{a_{24B}, a_{23}, d_9, d_{13}\}$), while investigating the number and types of simplices formation (e.g., 2vs.1), as well as the attacking and defending players located behind and ahead of the ball line. Such an analysis may provide coaches and performance analysts with relevant information regarding offensive and defensive patterns of team play.

****Please insert Figure 2 near here****

5.4 Most of the metrics used to model social interactions are based on paths, which can be inappropriate for sports contexts

An imperative step of the hypernetworks approach is to define, at each level of analysis, the significant relations that govern dynamics of competitive performance, and represent them utilising different criteria (e.g., modelling team dynamics through values of players' interpersonal distances) for

1 selecting the players in each set (i.e., linked by a hyperedge) [34, 36]. A major concern with such an
2 analysis is geographical proximity currently utilised for modelling team dynamics in hypernetworks. The
3 definition of such criteria will considerably limit all data analyses and interpretations of team sport
4 performance. It is an arduous and challenging task for researchers and sports scientists to seek and
5 explore novel ways of conceptualising and (re)defining such criteria, theoretically and mathematically,
6 based on characteristics of each team sport subjected to a multilevel approach. Another relevant issue is
7 the use of metrics that consider more than single relationships (either dyadic or hyperedges). Previous
8 studies (e.g. Borgatti [39]) have presented examples where using metrics based on shortest paths may not
9 be adequate. Using walks instead of paths [39] or even applying random walk Monte Carlo methods (e.g.
10 Cheng et al. [40]) for modelling social interactions may be worth considering.

11

12 **6 Conclusions and practical applications**

13 In this position paper, we highlighted how the multidisciplinary nature of complexity sciences, in contrast
14 to traditional sciences, supports explanations of complex phenomena emerging in sports performance
15 contexts. Under the umbrella of complexity sciences, and particularly SNA, multilevel hypernetworks
16 constitute promising frameworks for scrutinising the dynamical relations emerging in collective
17 interactions of competitive sport performance at several levels of analysis. Multilevel networks can
18 overcome major limitations of traditional network techniques, having the potential for expanding the
19 scope of analysis for studying team dynamics. They could provide more accurate information by
20 representing and understanding multilevel team behaviour dynamics, including micro (e.g., interactions
21 between players), meso (e.g., dynamics of a given critical event, e.g., a goal being scored), and macro
22 (e.g., interaction between sets of players) levels.

23

24 **Compliance with Ethical Standards**

25

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