

Review Article

Towards Understanding the Analysis, Models, and Future Directions of Sports Social Networks

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With the rapid growth of information technology and sports, a large amount of sports social network data has emerged. Sports social network data contains rich entity information about athletes, coaches, sports teams, football, basketball, and other sports. Understanding the interaction among these entities is meaningful and challenging. To this end, we first introduce the background of sports social networks. Secondly, we review and categorize the recent research efforts in sports social networks and sports social network analysis based on passing networks, from the centrality and its variants to entropy, and several other metrics. Thirdly, we present and compare different sports social network models that have been used for sports social network analysis, modeling, and prediction. Finally, we present promising research directions in the rapidly growing field, including mining the genes of sports team success with multiview learning, evaluating the impact of sports team collaboration with motif-based graph networks, finding the best collaborative partners in a sports team with attention-aware graph networks, and finding the rising star for a sports team with attribute-based convolutional neural networks. This paper aims to provide the researchers with a broader understanding of the sports social networks, especially valuable as a concise introduction for budding researchers interested in this field.

1. Introduction

Social networks such as Facebook, YouTube, Twitter, and Tumblr have attracted billions of users, many of whom share their daily activities on social network sites [1, 2]. Social network sites are defined as “web-based services that allow individuals to (1) construct a public or semipublic profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system” [3]. A sports social network is a social network with the characteristics of multidimensional interaction centered on sports, the independent selection of sports audiences, and the affinity of sports information dissemination.

Sports social networks analysis can bring many benefits to sports teams [4–9]. By analyzing the sports social network based on sports big data [10], its advantages can be reflected

at different levels: (1) In the case of personal sports, social network analysis is helpful to improve and enhance the individual competitive performance of athletes [11]. (2) In team sports, sports social network analysis can provide useful data support for team decision-makers in improving team competitive performance [12–14]. (3) For national sports, sports social network analysis can provide valuable information in improving national sports literacy and participation [15]. By using social network analysis, data mining, network science, and statistical techniques, some crucial problems have been explored such as team behavior dynamics and the trends of team performance [13, 16–21]. The social network analysis techniques such as centrality and its variants, entropy, and other metrics have been used in the passing network [22–24].

Many researchers have made meaningful attempts to analyze team behavior and performance, evaluate sports team behavior and performance, and predict sports team

behavior and performance by using sports social network models [5, 16]. We provide an overview of existing sports social network models in recent years. Typically, the core part of a sports social network model consists of social network analysis and machine learning algorithms, including an enhanced topic model, decision-making model, probabilistic model, gradient boosting, and regression [25–28].

The sports social networks have aroused widespread interest among scholars. Based on the sports social networks, researchers have actively explored team sports and made gratifying progress. This article presents and compares the recent research work on sports social networks. As far as we know, this article is the first to give a detailed overview of sports social networks. Our main contribution and organization are depicted in Figure 1:

- (1) In Section 2, we review the sports social network analysis, from describing the sports social networks (passing networks and transition networks) to categorizing analysis methods based on passing networks such as centrality and its variants, entropy, and clustering coefficient.
- (2) Section 3 reviews the sports social network models and categorizes these models by application category, including analyzing models, evaluating models, and predicting models. These models are primarily used in the study of sports team behavior and performance.
- (3) In Section 4, we discuss promising research directions in this rapidly growing field, such as mining the genes of sports team success with multiview learning, evaluating the impact of sports team collaboration with motif-based graph networks, finding the best collaborative partners in a sports team with attention-aware graph networks, and finding the rising star for a sports team with attribute-based convolutional neural networks. This article is concluded in Section 5.

2. Sports Social Network Analysis

In sports big data research, sports social networks are constructed to support sports social network analysis, providing meaningful guidance and help for team sports performance and revealing the relationship patterns in team sports [12, 25, 29, 30]. In this section, we start with the introduction of sports social networks, and then categorize and compare the analysis based on passing networks.

2.1. Sports Social Networks. The sports social networks consist of players, coaches, sports events, and sports fields. The sports events include ball sports such as football, handball, basketball, ice hockey, and other sports. The interaction between players can reflect the playing style of a team and the importance of individual players in their team [31]. Two representative sports social networks are listed as follows: passing networks (see Figure 2) and transition

networks (see Figure 3). Figure 2 shows a passing network including five players and the passes between football players. The arrow indicates the direction of the ball, and the number indicates the number of passes. Figure 3 shows a transition network consisting of two parts: a passing network and the outcomes of the passes. Player No. 5 shots the goal once and misses the goal once.

2.2. Analysis Based on Passing Networks. Analysis based on passing networks mainly deals with the data on the relationship between players, emphasizing the sports social network structure, driven by relational quantification occurring among them. The representative measure is centrality in the passing networks [32–36]. The analysis based on passing networks has undergone major shifts, from degree centrality [33] to flow centrality [37], from unweighed measures [38] to weighted measures [37, 39], and from homogeneous passing networks [40] to heterogeneous passing networks [32].

2.2.1. Centrality and Its Variants. Centrality is an important indicator to determine the importance of nodes in a network. In the past decade, sports social network analysis has undergone major shifts, from degree centrality [36] to eigenvector centrality [40, 41], from unweighed centrality measures [12, 42] to weighted centrality measures [37, 39]. In team sports, centrality is mainly used in the following aspects: (1) Identifying prominent players [33, 43]. (2) Determining the key pitch zones for matches [29]. (3) Understanding the team dynamics. Reference [32] (4) Predicting the sports team performance [34, 44] (see Tables 1 and 2). Table 1 shows the practical application of centrality in sports social network analysis from 2012 to 2017. Table 2 shows the practical application of centrality in sports social network analysis from 2018 to 2021. It should be noted that the centrality and its variants in Tables 1 and 2 are very representative applications in sports social network analysis in the past decade.

In sports social network analysis, frequently used unweighed centrality metrics include degree centrality [46], in-centrality, out-centrality [11], betweenness centrality, closeness centrality [38], and eigenvector centrality [48]. Sports team cohesion is positively related to team performance. The greater the cohesion of a sports team, the more outstanding the team’s performance [32]. Using social network analysis techniques, they not only demonstrate the network structure of team cohesion but also highlight each athlete’s position and centrality within the team. Two centrality metrics (in-degree centrality and out-degree centrality) are used to analyze the centrality levels of Portuguese positional roles and to identify the key tactical positions during the FIFA World Cup 2014 [35]. Game actions are taken as nodes, and their interactions are treated as edges. Eigenvector centrality is used to measure the importance of the nodes (game actions) in eight matches of the Men’s World Cup 2015 [41]. The relationship between passing networks, position variables, and team performance is explored by relying on closeness centrality and

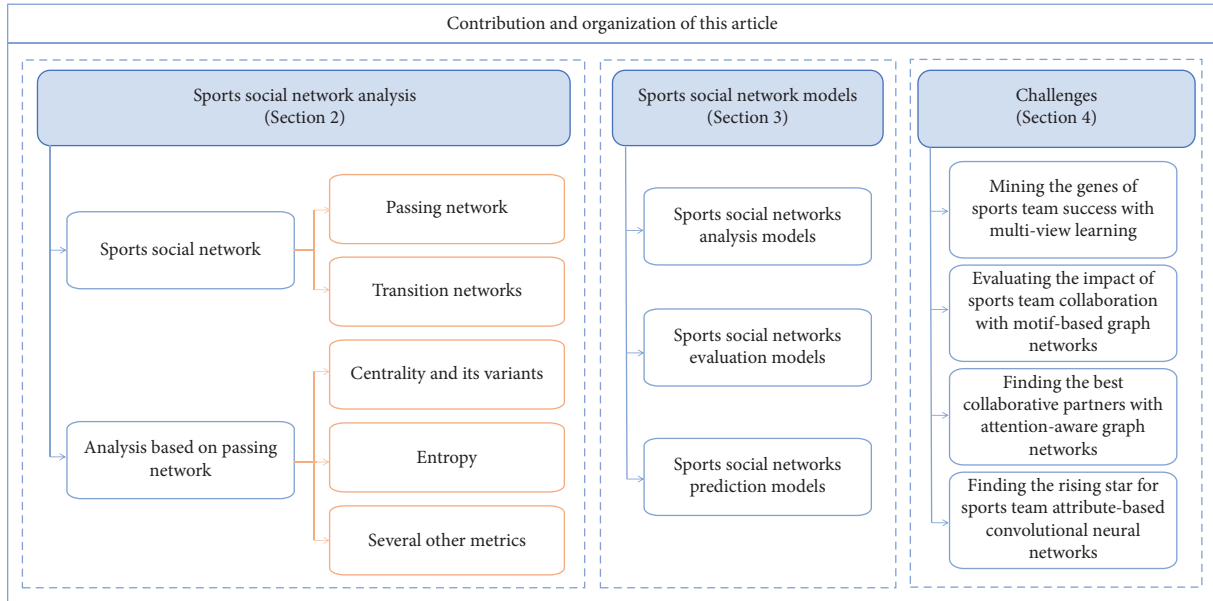


FIGURE 1: Contribution and organization of this article.

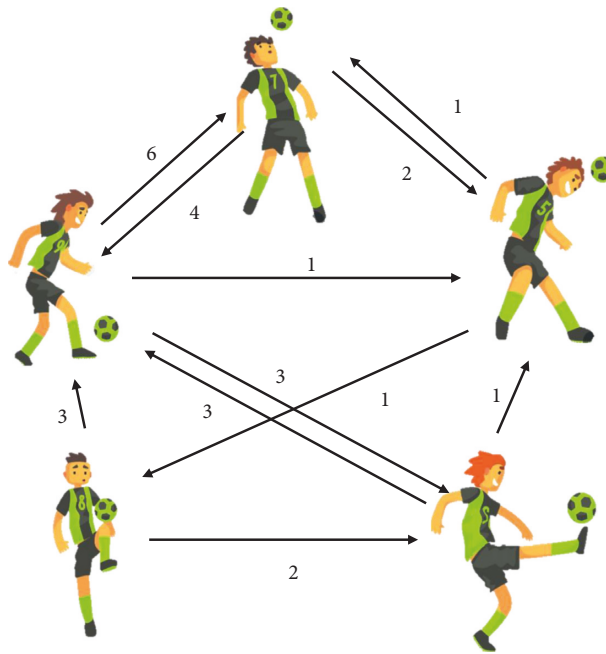


FIGURE 2: A small example for passing networks.

betweenness centrality [38]. Their research results show that higher intrateam well-connected passing relationships may improve team performance. A soccer win-lose predicting model is designed by using social network analysis and gradient boosting [44]. The experiment results demonstrate that the metrics related to centralities, such as degree centrality, eigenvector centrality, betweenness centrality, and closeness centrality can reveal the soccer team performance.

Some scholars have actively explored sports social networks and developed weighted centrality measures based on unweighted centrality measures, driven by the evolution of sports social networks. The weighted centrality indicators

mainly include weighted in-degree, weighted out-degree, weighted betweenness centrality, and weighted closeness centrality [39]. By comparing the network patterns of different team sports, Korte et al. [39] characterize the nature of team sports and find that the athlete’s tactical position affects the athlete’s level of performance. Korte et al. [37] identify the dominant player in football matches by applying a play-by-play social network analysis, driven by quantification of the interaction patterns between a player in a sports team. In their research, weighted betweenness centrality and flow centrality are used to understand the role of players in a football match. The flow centrality is closely related to the

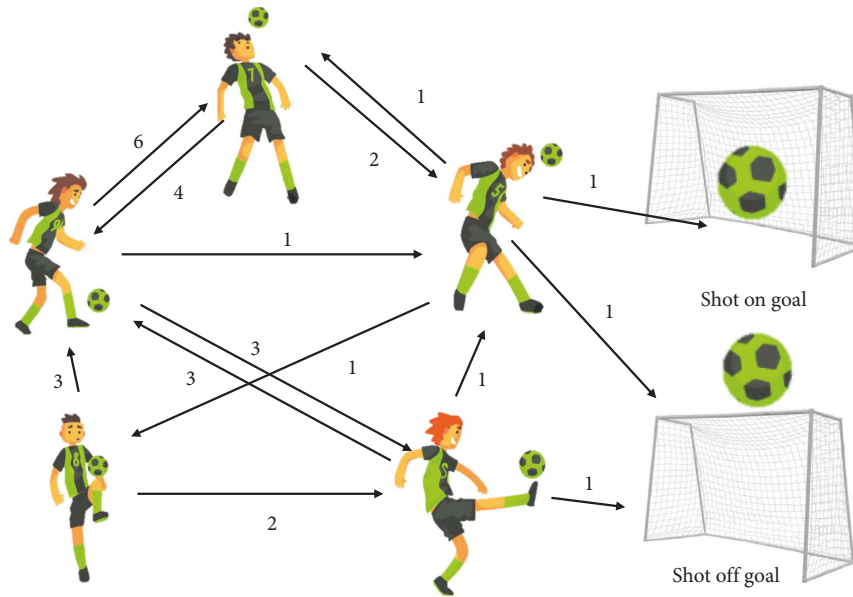


FIGURE 3: A small example for transition networks.

TABLE 1: Centrality and its variants for sports social network analysis from 2012 to 2017.

Centrality and its variants	References	Social network	Purpose	Advantages
In-degree centrality	[32]	Heterogeneous network	Understanding team dynamics	Easy to calculate
Degree centrality	[33]	Player passing network	Identifying the importance of football network	Easy to calculate
Degree centrality	[34]	Player passing network Zone passing network	Predicting the outcomes of games	Considering two passing networks
Scaled connectivity	[45]	Player passing network	Distinguishing the vertexes of players' network	Easy to calculate
In-degree centrality Out-degree centrality	[35]	Player passing network	Analyzing the centrality levels of Portuguese positional roles	Easy to calculate
In-degree centrality Out-degree centrality	[11]	Player passing network	Analyzing the leader's importance in the team	Easy to calculate
In-degree centrality Out-degree centrality	[36]	Position passing network	Identifying the centrality levels of players	Easy to calculate
Eigenvector centrality	[41]	Player passing network	Understanding the importance of each game action in overall performance	Considering the connection to the central nodes
Eigenvector centrality	[40]	Player passing network	Determining the tactical leader of a sports team	Considering the connection to the central nodes
Closeness centrality Betweenness centrality	[38]	Position passing network	Analyzing the relationship between players and individual and team performance	Considering the passing relationship in a team
In-degree centrality Out-degree centrality Betweenness centrality	[43]	Position passing network	Identifying prominent players	Easy to calculate

betweenness centrality. The flow centrality is measured by the proportion of plays that are involved in at least once relative to all plays by a sports team [37].

2.2.2. *Entropy*. Shannon's entropy is used to calculate the uncertainty of the team's numerical advantage across sub-areas [50]. The highest uncertainty appears in the center-

TABLE 2: Centrality and its variants for sports social network analysis from 2018 to 2021.

Centrality and its variants	References	Social network	Purpose	Advantages
Degree eigenvector Betweenness closeness	[44]	Position passing network	Predicting the soccer team performance	Using several network indicators
Weighted in-degree Weighted out- degree Weighted betweenness Weighted closeness	[39]	Position passing network	Characterizing different team sports	Using several network indicators
In-degree Out-degree	[29]	Goal scoring passing network	Determining the prominent pitch zones for a match	Using several network indicators
Within-degree Degree scaled connectivity	[42]	Position passing network	Providing help for team performance	Using several network indicators
Flow centrality Flow betweenness Weighted betweenness	[37]	Position passing network	Identifying dominant and intermediary players	Considering the temporal order of passing network
Degree centrality	[46]	Position passing network	Analyzing network centrality variation between playing positions	Considering passing sequences
In-degree Out-degree stress centrality Betweenness Closeness	[47]	Position passing network	Identifying the passing performance	Better understanding team's attacking properties
Eigenvector centrality In-degree Out-degree Closeness	[48]	Zone passing network	Analyzing the attack in volleyball	Better understanding team's attacking properties
Betweenness Eigenvector centrality In-degree Out-degree Incloseness	[12]	Position passing network	Investigating cooperative passing interactions	Understanding cooperative passing network
Outcloseness Betweenness Eigenvector centrality	[49]	Position passing network	Analyzing the physical activity	Understanding the relational structure of the adolescent

middle subareas, reflecting the dynamic shifts of players from adjacent subareas to target subareas. To better understand the consequences of different tactical behaviors in basketball games, it is necessary and important to analyze the team behavior. Variability analysis provides a solution for this purpose and what is used to evaluate variability analysis is Shannon entropy [51]. By analyzing the variability of setting conditions, attack zone, and attack tempo, the findings suggest that uncertainty in attacking actions in competitive games may produce better outcomes only when other game actions are stable. Shannon entropy is used to reveal collective tactical behaviors in volleyball teams to analyze the final team rankings, finding that the highest-ranked teams show greater unpredictability in tactical performance measures such as attack tempo and block opposition [52]. The dynamics of a national soccer league are analyzed by entropy, mutual information, and Jensen–

Shannon divergence [53]. It should be noted that entropy and mutual information are used as the phase variables of a soccer league season. The novel entropy models including relative transition entropy and network transition entropy are presented in team sports networks [54]. Their experimental results show that the individual and team transition entropies values of the winning team are greater, indicating that more unpredictable teams may be closer to success.

2.2.3. Several Other Metrics. In graph theory, the clustering coefficient describes the degree of clustering among vertices in a graph. The global clustering coefficient and local clustering coefficient have been used in team sports research. In sports teams, the higher the clustering coefficient for an athlete, the better the cooperation and interaction between the athlete and other athletes [45]. The clustering coefficient

is used as an indicator of the local robustness of the passing network [25]. In addition, density, heterogeneity, and centroid players are used to analyze the teammates' cooperation in a sports team [33]. The experimental results show that the network metrics such as density, heterogeneity, and centroid player can characterize the teammates' interaction in a sports team.

3. Sports Social Network Models

Figure 4 shows a framework for modeling the team behavior and team performance, including three parts: input, model, and output. Individual behavior and performance, team behavior and performance, and other data are often used as input for sports social network models. The modeling process mainly includes two aspects: social network analysis and machine learning algorithm. In terms of social network analysis, the following methods are frequently used such as centrality and its variants, entropy, and clustering coefficient. The social network analysis model is mainly used in the following three aspects: (1) analyzing sports team behavior dynamics and team sports performance; (2) evaluating sports team behavior and performance; (3) predicting team behavior and performance.

In team sports research, analysis of team behavior and team performance is important and meaningful. In the past ten years, researchers have made some remarkable achievements in this field (see Table 3). In team sports performance analysis, the sociobiological models are adopted to explain how repeated interactions between the players occur [55]. A spatiotemporal bilinear basis model is used to form a compact spatiotemporal representation to find the behavior patterns of a team associated with the match events [56]. A team tactic topic model is developed to learn the latent tactical patterns, modeling the locations and passing relationships between players simultaneously in soccer teams [57]. A visual analytics workflow is proposed to detect and explore the interesting characteristics of team sports [56]. In their research, several classification models are used, including logistic model tree, logistic base, functional tree, decision stump, and support vector machine, to select the interesting situations and divide the interesting and uninteresting intervals in team sports. Two representative decision-making models are introduced, including the adaptive dynamics and the imitation dynamics, to analyze the evolutionary game dynamics [58]. In the adaptive process, the players can adaptively adjust their strategies towards the maximum of the payoffs. The players adjust their strategies by imitating the strategies of their neighbors in the imitation process. The experimental results show that the feedback from neighborhoods to each player can alter the tendency of defection for adaptive dynamics [58]. The dynamic analysis model of soccer teams is proposed to analyze the team's behavior by using two models, one model explores the power-law behavior and fractional-order integration for team dynamics, and the other model uses to interpret the league season [27]. Based on more than 6000 games and 10 million events in six European leagues, a relationship model is proposed for

quantifying the relationships between performance and success, indicating that a soccer team's typical performance is significantly related to the success of the team [59]. A multilevel hyper networks model is proposed, including three levels of analysis, to capture the key properties of synergies for understanding the competitive team performance [60].

Evaluation is another important application of the sports social network model. The Bayesian nonparametric models are proposed to characterize the instantaneous strategies in a competitive dynamic game, indicating that it is possible to quantify the instantaneous dynamic coupling between agents [61]. Their experimental results suggest that the proposed model offers a natural set of metrics for facilitating analysis at multiple timescales and gives a method for assessing the social behavior. Based on the back-propagation neural network and the uncrossed analytic hierarchy process, a team performance evaluation model was developed to analyze and model the team cooperation and performance evaluation [60]. Based on the tactical features of position tracking data, a team performance model is proposed to assess the relationship between tactical behavior and match performance in the professional soccer match [62].

Compared with the evaluation, it is more meaningful to predict the performance and behavior of sports team members. The probabilistic graphical models are used to describe the generative process of the collective behavior, including two aspects: inferring the individual player behaviors to decompose the collective behavior and learning individual player's behaviors to predict the collective behavior [26]. A predictive framework for a soccer win-lose system is developed by using the social network analysis techniques and gradient boosting [44]. The proposed framework is compared with a support vector machine, neural network, decision tree, case-based reasoning, and logistic regression. The results show that the soccer win-lose prediction framework can represent the soccer team's performance. An elite Netball Performance Model is developed to identify complex relationships, including inter-related objects, processes, and values [28]. Based on the individual performance model and team performance model, an information-rich passing network model is proposed to optimize the passing network by relying on the suppression function [63]. The proposed quantitative method combines coordination, adaptability, flexibility, and tempo into a passing network to mine the efficient strategy for football social networks. A coarse-grain activity model is developed to represent a passing network, and based on this passing network, a novel prediction model is developed to predict the likelihood of a team, attempting to score at a certain stage of the match [64]. The experimental results show that the proposed model has high accuracy in predicting the correct segmental outcome for soccer matches. The collective team behaviors and team performance analysis of elite rugby competition are two important aspects of team sports. Two models are developed to deal with the tasks mentioned above. One is the mixed-effects multinomial regression model to identify the differences between positional groups; the other model is the mixed-effects

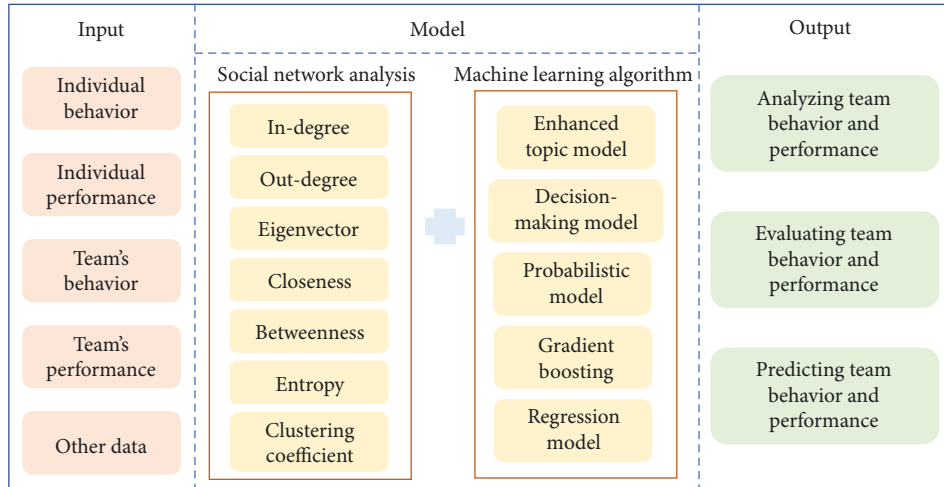


FIGURE 4: A framework for sports social network models.

TABLE 3: Representative models for sports social network analysis from 2012 to 2021.

Models	References	Social network	Homogeneous or heterogeneous network	Purpose
Sociobiological models	[55]	Players passing network	Homogeneous network	Analyzing team sports performance
a spatiotemporal bilinear basis model	[56]	Position passing network	Homogeneous network	Forming a compact spatiotemporal representation
An enhanced topic model	[57]	Position passing network	Homogeneous network	Discerning the tactical patterns of sports team
Classification model	[65]	Position passing network	Homogeneous network	Selecting the interesting situations, and dividing the interesting and uninteresting intervals
Decision-making models	[58]	Complex network	Homogeneous network	Analyzing the networked game dynamics
Probabilistic graphical models	[26]	Position passing network	Homogeneous network	Describing the generative process of the collective behavior
Probabilistic models based on the concepts of fractional calculus	[27]	Position passing network	Homogeneous network	Describing the complex behavior dynamic of soccer teams
Gradient boosting	[44]	Position passing network	Homogeneous network	Designing a soccer win-lose prediction system
Information-rich passing network model	[63]	Players passing network	Homogeneous network	Developing an efficient strategy for a higher winning rate in match
Regression model	[12]	Position passing network	Homogeneous network	Analyzing the collective team behaviors and performance toward successful team performance

binomial logistic regression model to determine the relationships between team-level network metrics and match outcomes [12].

4. Open Issues and Challenges

4.1. Mining the Genes of Sports Team Success with Multiview Learning. Mining the genes of team success is to mine the key factors that drive the success of sports teams, which may

be explicit or implicit. Most importantly, these factors drive the team's success in the game. It is an important and challenging task to discover the decisive factors that drive the victory of the game. Sports social networks have undergone a transformation from homogeneous networks to heterogeneous networks, from unstructured quantification to structured quantification. How to construct a heterogeneous sports social network, how to model heterogeneous team behavior and interactions among different sports entities,

and how to use structured quantitative methods to explore the genes of team success is a meaningful and challenging task. The multiview learning and heterogeneous sports social relationship representation may provide a solution.

4.2. Evaluating the Impact of Sports Team Collaboration with Motif-Based Graph Networks. Research on team sports mostly focuses on team sports behavior evaluation and team performance evaluation. However, little attention has been paid to the evaluation of the impact of sports team collaboration. Like soccer and basketball, both are team sports, and collaboration between players can lead to unexpected results, such as scoring goals. The impact of athlete collaboration is an important aspect of team performance evaluation. The impact evaluation of athlete collaboration affects not only the team's performance but also whether the sports team can develop sustainably. Therefore, how to construct heterogeneous collaboration networks, and how to quantify the impact of sports team collaboration is challenging. The motif-based graph networks can represent the higher-order relationships, and structured quantitative models such as PageRank may provide a solution for assessing the impact of sports team collaboration.

4.3. Finding the Best Collaborative Partners in Sports Teams with Attention-Aware Graph Networks. Few researchers focus on the best partners in sports teams. However, each athlete in a sports team has one or several best partners. By collaborating with the best partners, this athlete may score goals or provide a great opportunity to score goals. Each athlete works with the best collaborator in each game, which perhaps produces the best results. The best results are likely to occur if each athlete can attack or defend with the best partner in each game. Therefore, the study of who is the best partner of an athlete is a meaningful and challenging task. Constructing an attention-aware graph network of athlete collaboration pairs, and applying structured quantitative methods may offer a solution.

4.4. Finding the Rising Star for a Sports Team with Attribute-Based Convolutional Neural Networks. The sustainable development of a sports team not only depends on the elite athletes in the team but also on constantly mines rising stars in the team. A rising star in a sports team refers to an athlete at the beginning of their career who is very likely to become an elite athlete in the future, namely the core athlete of a sports team. Finding the rising star not only contributes to the sustainable development of sports teams but also guides the allocation of national funds. However, so far, based on sports social networks, little literature has studied how to mine, evaluate, and predict rising stars of a sports team. How to construct sports social networks, and how to use sports social network analysis technology and modeling method to solve this problem is a challenging task. Based on the genes of sports team success, different types of attributes of team members, and the convolutional neural networks may provide a solution.

5. Conclusion

In this paper, we provide a comprehensive review of sports social networks, focusing on sports social network analysis, sports social network models, and open issues and challenges. There are several shifts in the sports social network area: (1) from homogeneous social network analysis to heterogeneous social network analysis; (2) from simple centrality measure to data-driven team performance prediction; (3) from team behavior analysis to team behavior prediction. Although researchers have offered some analysis methods and models for sports social networks, the solutions to some key issues remain unknown, such as mining the genes of sports team success with multiview learning, evaluating the impact of sports team collaboration with motif-based graph networks, finding the best collaborative partners in a sports team with attention-aware graph networks, and finding the rising star for a sports team with attribute-based convolutional neural networks.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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