



From core to peripheral: A network analysis of lineup types in NBA playoff teams

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ABSTRACT

This study aims to identify the types of lineups based on their topological structure within a lineup network and to explore the relationship between lineup types and team standings during 10 NBA playoff seasons from 2012-2013 season to 2021-2022 season. A total of 15,699 lineups from 1,655 playoff games were collected to construct lineup networks. Three roles of the lineup, called core, connector and peripheral lineups, were found through community detection and unsupervised clustering of within-community degree, participation coefficient, and playing time. The percentage presence of connector lineups showed a positive correlation with the number of playoff wins ($r = 0.45, p < 0.001$), while peripheral lineups demonstrated a negative correlation ($r = -0.33, p < 0.001$). Additionally, the study found that connector lineups were more frequently reused than peripheral lineups ($H = -14.90, p < 0.001$) and that stronger teams exhibited lower conserved rates of all kinds of lineups. The collective performance was found to be more dependent on connector lineups ($H = 926.42, p < 0.001$) than peripheral lineups ($H = 3342.63, p < 0.001$). This study is the first to provide insights into the global lineup roles within season-scale lineup structures, offering generalizable suggestions for optimizing rotations. These suggestions advocate for the inclusion of more connector lineups and versatile players, and a reduction in the reuse rate of lineups, especially those classified as peripheral.

Introduction

The outcome of basketball games is not only subject to players' abilities and on-court improvisation capacities, but also heavily depends on off-court decisions such as lineup adjustment [1]. The coaches aim to maintain a competitive advantage by properly using lineups under different contexts [2,3]. Lineups can be intuitively categorized as core lineups and others. Core lineups are usually characterized by a powerful and fixed composition of players, with more competition time and opportunities. Other lineups, by contrast, vary widely in terms of competitive situation and receive less play-time. The high efficiency of core lineups is however thwarted by aspects of stamina [3], leading coaches to constantly make compromises when adjusting the lineups [4]. Both types of lineups are indispensable for winning games, especially for long-term performance. This naturally raises the question as to

how the stronger teams tackle this problem and use different lineups.

Only a few studies have discussed this important question. In recent years, data-driven studies have focused on lineup optimization [5] by considering different factors, typically lineups' efficiency [6,7]. It was found that bench players of the best teams had a positive impact on the team, and the performance of the weak teams were more reliant on their starters' performances [8]. The non-starters from strong teams thus seem to be able to impact the team's performance more than from weaker teams, which generally highlights that coaches should better develop each player in their rosters.

In view of these findings, exploring lineup usage should provide more precise general suggestions for better utilization of different lineups. To achieve this goal, we first need to capture a team's characteristics of making lineup-adjustment decisions. Coaches use a new lineup by substituting several players from the current lineup [9], thus

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we can explore the usage style of teams from the substitution-based associations between lineups. Lineups within one team are collectively motivated to win the games and share limited competition time. Above all, we can properly categorize lineup types [10] by modelling all the lineups from one team as a whole system [11] and considering the substitution relationship and competition time. Complex network models are a powerful tool to model the interrelationship between individuals and have been widely applied to team sports [12,13]. They are known to be appropriate to model lineups [14] and substitution-based connections as lineup network. A complex network also bears the potential to quantify a team's lineup adjustment strategy by using multiple network measurements. Furthermore, because coaches change only one or two players of the current lineup in most cases, certain lineups may connect only to others with similar player compositions. Compared to ordinary networks in team sports [15,11], the distribution of substitution-based connections between lineups is more heterogeneous, and the whole network may be easily divided into several "communities", where lineups densely connect with each other. In such case, it is more meaningful to consider a node in its "community" than in the whole network for determining the lineup types [16]. For all these reasons, we will use network models to study the roles of lineups in this paper.

In order to explore how elite basketball teams use different types of lineups, we start by building season-scale lineup networks for each playoff team between the 2012–13 and 2021–22 NBA seasons, with player substitutions as links. We then determine the lineup types according to their topological feature and competition time. Based on the obtained lineup types, we calculate the relationship between teams' standings and the different types of lineups, and we figure out how strong teams reuse lineups in different games. Our study is meant to help coaches to quantitatively understand lineup types and aims to provide general suggestions for making better use of lineups.

Method

Data

Archival data were obtained from the public official NBA website (available at www.nba.com/stats) through a publicly available Python toolkit *nba_api* (available at github.com/swar/nba_api).

We extracted lineup information from the play-by-play data using a two-step pipeline, which also served as a quality control mechanism: (1) Determining the starting lineups for each quarter (excluding overtime): We identified the starting players by counting those recorded in the events until five players were identified for each quarter. It is important to note that a player might be substituted before the starters are fully determined, or no events might be recorded before a player leaves the field. (2) Inferring subsequent lineups based on starters and substitution events: This step involved addressing two specific scenarios. First, multiple players might be substituted simultaneously, particularly after timeouts. In such cases, we only recorded the final lineup to exclude any intermediate, non-existent lineups. Second, players entering the game after an ejection were not officially recorded as a substitution event.

This two-step pipeline helped us identify various extreme cases that could affect the accuracy of the extracted data. For instance, if our inferred lineup had only four players, this indicated a potential missing substitution event, such as an ejection. Additionally, the absence of a player in the current lineup who was recorded as being replaced suggested potential errors in determining the starters. We must also ensure that the end time of the previous lineup matches the start time of the following one. A total of 15,699 lineups from 1655 playoff games between the 2012–13 and 2021–22 NBA seasons were collected.

We obtained the temporal switches of lineups during the games, treating each pair of temporally adjacent lineups as nodes and establishing an edge from the previous lineup to the subsequent one. Links are weighted by the frequencies of substitution between certain pairs of

lineups. Lineup information of each playoff team t is defined as $L_t = \{l_i, d_i | i \in [1, N_t]\}$, where lineup l_i played for a competition time d_i per game, and there are in total N_t lineups for that team. For each playoff team in each season, we built a lineup network for all the lineups presented by that team in the playoffs, as shown in Fig. A2, by using the python toolkit *networkx*. This resulted in 160 lineup networks from 16 playoff teams per year over 10 seasons.

Identification of lineup roles by detecting communities of lineup network

Based on the lineup network, we categorize lineup types according to their topological features. As can be appreciated from Fig. 1(a), the links between lineups are more uneven compared to other types of networks such as the player substitution network of Fig. 1(b), even though they are built based on the same team's data. This is natural, as hundreds of lineups in Fig. 1(a) can be organized by a dozen players (see Fig. 1(b)). Numerous lineups locally connect to a small part of the network to form sub-networks, where lineups are usually similar in player composition and functions. This kind of network feature has also been found on metabolic networks [16] where metabolites related to similar metabolic processes were bound together, as well as on air transportation networks [17]. Based on these studies, we thus consider the connection features of lineups within their own sub-networks as well as with other sub-networks.

Specifically, the procedure of categorizing lineup types contains two sequential parts: (i) finding the different lineup communities in which the lineups are more densely interconnected with each other than with the rest of the network; (ii) identifying the lineup roles according to the patterns of inter- and intra-community connections (see below for definitions). Consider a lineup network as in Fig. 2(a). Regarding the first part, we show in Fig. 2(b) the outcome of applying the Clauset-Newman-Moore (CNM) greedy modularity maximization algorithm [18] to find the communities where nodes densely gather for each lineup network. The CNM community detection algorithm optimizes modularity by iteratively merging pairs of communities, resulting in more stable outcomes compared to initial-value-sensitive methods like Louvain [19] and Label Propagation [20] algorithms. Additionally, CNM has been increasingly adopted on small-scale [21–23] and sparse networks [18]. The role identification is illustrated in Fig. 2(c) but requires more explanations.

Consider that as a result of community detection, lineup l_i is detected to belong to community c_j , and k_{ij} is the number of links of lineup l_i to other lineups in community c_j . Subsequently, we can determine the lineup types according to their inter- and intra-community connections. Let \bar{k}_{c_j} denote the average number of lineup links in c_j , and $\sigma_{k_{c_j}}$ the corresponding standard deviation in c_j . The within-community degree of lineup l_i is defined as a form of z-score:

$$z_i = \frac{k_{ij} - \bar{k}_{c_j}}{\sigma_{k_{c_j}}} \quad (1)$$

It measures how well-connected lineup l_i is to other lineups in its community and hence yields the intra-community connection of l_i .

As for the connection pattern of lineup l_i with all lineups of different communities, we define the participation coefficient p_i of lineup l_i as

$$p_i = 1 - \sum_{j=1}^{N_c} \left(\frac{k_{ij}}{K_i} \right)^2, \quad j \in [1, N_c], \quad (2)$$

where K_i is the total degree of lineup l_i and N_c the total number of detected communities. The participation coefficient, or inter-community connection, of a lineup is therefore close to 1 if its links are uniformly distributed among all the communities and 0 if all its links are within its own community.

These two network measurements are then calculated for each lineup to represent their connecting pattern within the whole network. For

(a) **Lineup Substitution Network**

(b) **Player Substitution Network**

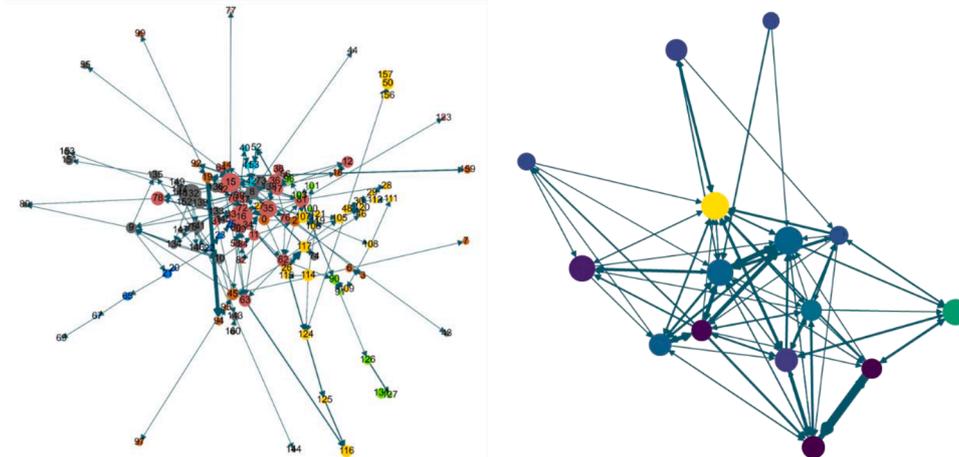


Fig. 1. Illustration of (a) lineup substitution network and (b) player substitution network of the same playoff team. (Golden State Warriors 2021–2022 playoffs).

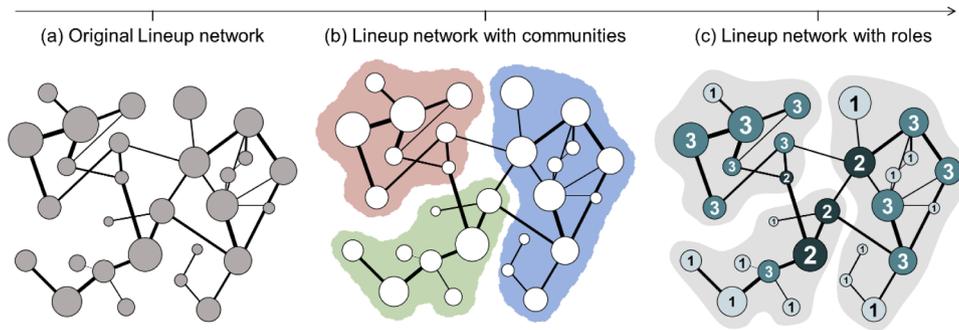


Fig. 2. The illustration of finding lineup roles. Given the network (a), community detection is used to categorize nodes into their communities as shown in (b), and next the types of nodes are identified according to their patterns of inter- and intra-community connections, see (c), where 1 refers to peripheral lineups, 2 connector lineups and 3 core lineups.

example, a lineup with high value of z_i can be expert in a certain competitive situation, while a lineup uniformly connected to multiple communities, hence with high value of p_i , may be more versatile.

The competition time of lineups is essential for determining different lineup types. We extract the playing minutes per game of each lineup from play-by-play data. We then apply an unsupervised two-step cluster algorithm [24] with log-likelihood as distance measure to detect lineup types, where we use as input the within-community degree z_i , the participation coefficient p_i and playing minutes per game. Given the lineup types, a team’s lineup structure can be observed from the number of different types of lineups. Insightful correlations can be drawn through analysis between the percentages of the different types of lineups in a team and the team’s standings to explore the characteristics of lineups from different levels of teams.

Another factor that mirrors the importance of a lineup is the probability of a team to reuse lineups in different games. To this end, we define a conserved rate cr_i of lineup l_i as

$$cr_i = \frac{ng_i}{Ng_t} \quad (3)$$

where ng_i is the number of games where lineup l_i received opportunities to play and Ng_t is the number of games the team has played. This further allows us to calculate the average conserved rate of each team over all types of lineups and to explore how a team’s reuse of lineups influences their standing.

Statistical analysis

We first carry out the Kolmogorov-Smirnov normality test for team’s standings, percentages and conserved rates of the types of lineups. According to the results shown in Table 1, we conduct the Spearman’s correlation test to explore the relationship between the percentages of types of lineups and teams’ standings, and the Kruskal-Wallis H test to examine (i) the difference of conserved rate between the obtained lineup types and (ii) the variation of conserved rate between teams with different playoff wins. All the statistical procedures are carried out on IBM SPSS Statistics for Windows Version 26.0. Armonk, NY: IBM Corp with a statistical significance level of 0.05.

Table 1
Results of Kolmogorov-Smirnov normality test.

	Statistic (D)	Significance
Team standings	0.182	<0.001
Percentage of peripheral	0.060	0.200*
Percentage of connector	0.069	0.061
Percentage of core	0.079	0.018
Conserved rate of peripheral	0.162	<0.001
Conserved rate of connector	0.164	<0.001
Conserved rate of core	0.066	<0.001

Results

The lineup roles of NBA teams

Three types of lineups were found by clustering the z_i , p_i and playing minutes per game. We label the first type of lineups as peripheral lineups, as they play an average of 0.51 min per game and present values of -0.02 of z_i and 0 of p_i . Peripheral lineups only own within-community links and are rarely used. The second type is termed connector lineups and has comparable playing minutes as peripheral lineups, but they exhibit the highest p_i (0.76) and lowest z_i (-0.52), suggesting that they are extensively connected with other communities. Hence the name connector. The last category, core lineups, plays the longest duration per game with an average of 4.91 min and exhibit a much higher z_i of 6.95 than the other two clusters, with a moderate magnitude of p_i (0.39). We refer the reader to Fig. 3 for more details.

The relationships between percentages of types of lineups and team standings during playoffs

Spearman’s correlation test was applied to explore the relationship between the team’s playoff records and percentages of three lineup clusters within that team. As shown in Fig. 4, teams with more playoff wins own a significantly higher percentage of connector lineups ($r = 0.45^{**}$, $p < 0.001$) and fewer peripheral lineups ($r = -0.33^{**}$, $p < 0.001$). The percentage of core lineups presents no significant correlation with the team’s playoff performance ($r = -0.12$, $p = 0.14$). These findings indicate that stronger teams tend to have more connector lineups and fewer peripheral lineups compared to weaker teams.

The difference in conserved rate between lineup types and teams

We tested the difference in conserved rate between the three obtained types of lineups and found a significant difference ($H = 2519.883$, $p < 0.001$). The results of post hoc pairwise comparison were shown in Table 2 and Fig. 5(a). Furthermore, we observe how the conserved rate

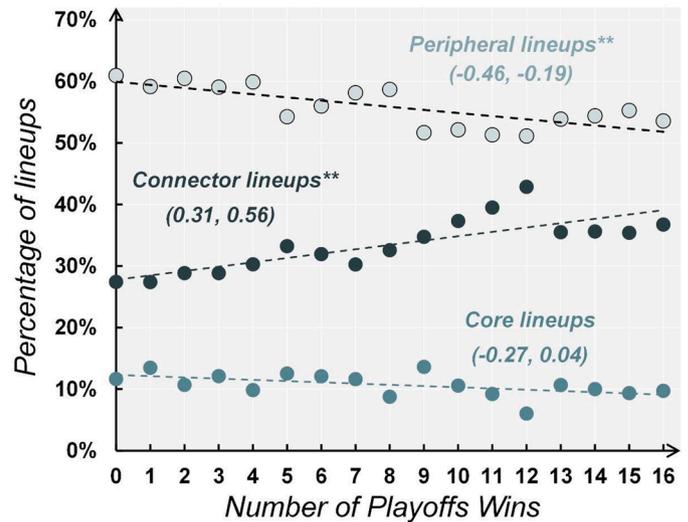


Fig. 4. The 95 % confidence intervals of correlation coefficients between numbers of playoff wins and percentages of the three types of lineups.

Table 2

Result of post hoc test about conserved rate between lineup types.

	Test Statistic	Standard error	Standard test statistic (Z)	Sig.	Adj. Sig. ^a
Peripheral-Connector	-1028.09	69.00	-14.90	.000	.000
Peripheral-Core	-5205.74	103.91	-50.10	.000	.000
Connector-Core	-4177.65	110.32	-37.87	.000	.000

^a Significance values were adjusted using the Bonferroni correction method for multiple comparisons.

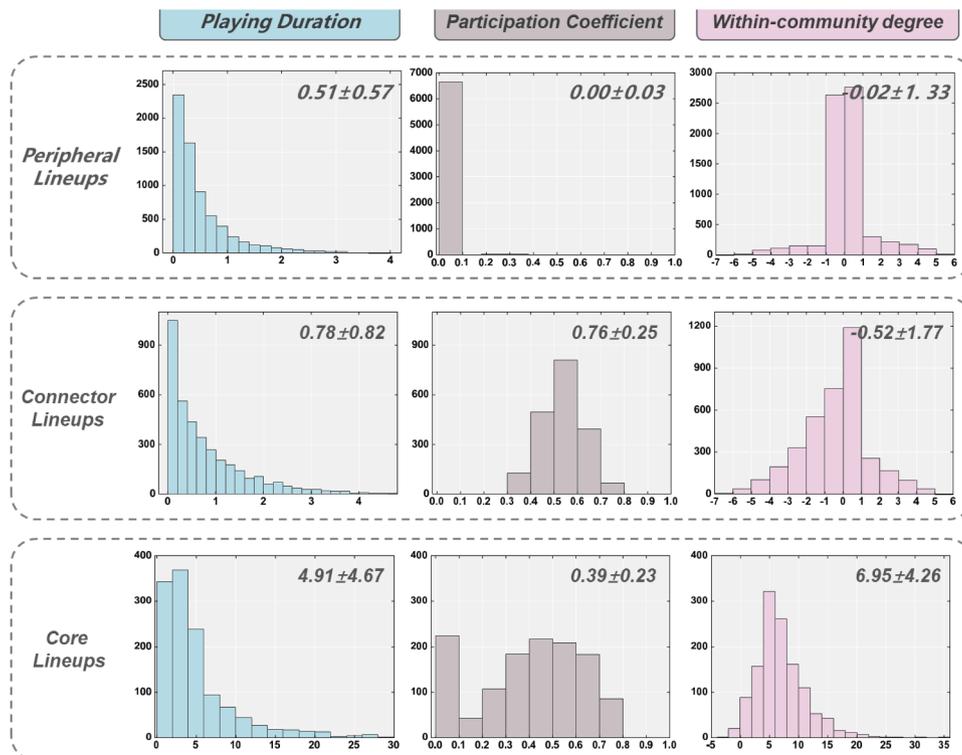


Fig. 3. The distributions of the three clustering variables within the obtained three lineup roles.

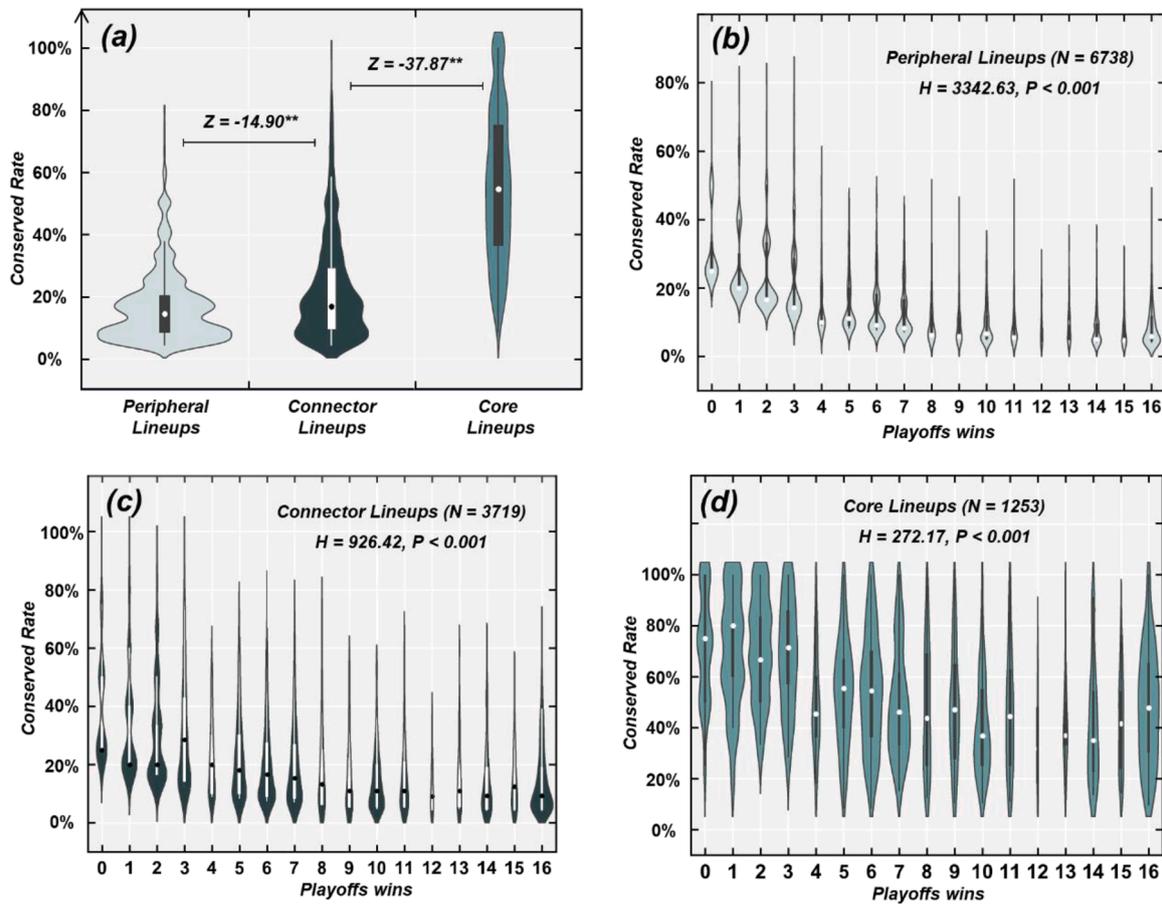


Fig. 5. The difference of conserved rate between (a) lineup types (Z is the standard test statistic) and (b-d) teams with different numbers of playoff wins for each lineup type. The distribution of conserved rate can be observed from each density curve, where the width corresponds to the frequency of lineups in each region. The box plot in the middle of each density curve shows the first and third quartiles (rectangle) and the median (dot).

varies with increasing playoff wins, as shown in Fig. 5(b-d). Peripheral lineups present the most significant decrease with an H of 3342.63 ($p < 0.001$), followed by the connector lineups with H of 926.42 ($p < 0.001$). The decreasing tendency of core lineups' conserved rate is significant yet less obvious with an H of 272.17 ($p < 0.001$).

Discussion

Based on the adapted lineup network, this study has aimed to categorize the different types of lineups and at exploring the relationship between lineup types and season-level competitive performance. The results show that the percentage of connector lineups within NBA teams is positively correlated with the teams' playoff wins, while for the peripheral lineups the opposite holds (both results are statistically significant). Regarding the comparison of conserved rate, connector lineups are more reused than peripheral lineups. Although the overall conserved rates of stronger teams are lower than those of weaker teams, the peripheral lineups tend to be abandoned across the playoff games.

The conclusions drawn from this study could generally provide suggestions for evaluating and integrating basketball lineups, in the sense that teams should add connector lineups and avoid overusing the peripheral lineups. To achieve this, teams should involve more versatile players in rotations or further develop the players currently on their roster. By doing so, more effective lineups could be generated against variable rivals.

Types of basketball lineups and playoff wins

Three types of lineups have been obtained based on their topological

structures: core lineups, connector lineups, and peripheral lineups. Core lineups have emerged as the most dominant within their respective communities with the longest playing duration. However, their percentage exhibits no significant correlation with the number of playoff wins. The primary difference among teams lies in the composition of non-core lineups. Stronger teams possess a significantly higher number of connector lineups, which strengthen the links between lineup communities. By contrast, weaker teams have more peripheral lineups, which might be generated by occasional decisions and are only used under specific contexts. The obtained results are in line with our previous work [11], which similarly indicated that the percentage of core players does not correlate with teams' standings. Strong teams also have a higher proportion of players with low vulnerability, suggesting a more evenly distributed influence throughout the whole substitution network.

Within the ten seasons involved in this study, $53.56\% \pm 4.62\%$ lineups from teams with 16 playoff wins were peripheral lineups, against $60.95\% \pm 9.15\%$ from teams with 0 playoff wins. The difference can be observed more clearly from specific teams. The Golden State Warriors of the 2014–15 season won 16 playoff games with a lineup composition of 0.51–0.42–0.07 (peripheral – connector – core), and the Dallas Mavericks of the 2019–20 season, with a lineup composition 0.67–0.21–0.12, won 2 playoff games. The percentage of peripheral lineups from the Mavericks was much higher than their connector lineups compared to the Warriors from the 14–15 season. We complement this information visually by giving the distribution of lineup types for the 2021–22 season playoff teams in Fig. A1 (Appendix section).

Nodes with more betweenness or connectivity are usually considered important. The central midfielder has been proved to be important for maintaining the connectivity of the football passing network because

they are usually highly connected with other players [25]. In the metabolic network [16], the nodes connecting with many communities were found to be the most conserved across species. These nodes were potentially characterized as versatile [26] to integrate different functional modules. In this study, the communities within the lineup networks contained temporally adjacent lineups with similar functions. Lineups from one community may only be used under a particular situation if the community is highly separated from the rest of the network. By contrast, the connector lineups connect with many other communities, which implies that they might appear under more circumstances. If more connector lineups were used, more players, especially non-starters, would be involved in these versatile lineups, which improves the robustness of the team's performance because of the low cost of changing lineups [27]. In an extreme case, if all the lineups were equally connected, none of the sub-networks would be found and each lineup would ideally own the same comprehensive abilities.

The playing styles of basketball players seem to be quite varied, as numerous studies [28–31] have recategorized the roles of players based on their game-related statistics to represent their playing styles [32]. In particular the versatile players from some practical lineups have caught researchers' attention [10]. To the best of our knowledge, the present study is the first to explore how to divide lineups' roles, and we have found a positive correlation between the percentage of connector lineups and teams' standings, from which a new insight might be derived to understand the composition of efficient lineups [10].

The difference in conserved rate between lineup types and teams

We use conserved rate to measure to what extent the lineups are reused among playoff games. Not surprisingly, the core lineups are the most conserved, followed by the connector lineups and then only the peripheral lineups. With the improvement of teams' records, stronger teams generally reuse fewer lineups regardless of their roles. Connector and peripheral lineups can be considered as non-core lineups because of the closeness of their playing time (0.78 min for connector and 0.51 min for peripheral lineups). However, the conserved rates of peripheral lineups decrease more significantly with the increase of playoff wins compared to the conserved rate of the connector lineups, demonstrating the importance of connector lineups for winning games.

Using more connector lineups may fundamentally increase the robustness of the collective performance. The degrees of a lineup network with more connector and less peripheral lineups are more well-distributed, rendering the team tougher against targeted tactics from the rivals during playoffs. By contrast, excessive reliance on certain lineups can weaken the collective performance, because once they are isolated, the connectivity of the network will largely decrease. The found overall tendency of being less dependent on individual lineups is consistent with previous studies about other applications of complex networks [33,34]. We determined the lineup types according to their inter- and intra-community pattern and found the correlation between team standings and the number percentage of non-core lineups. Coaches cannot arrange specialist lineups against each situation, more versatile players should be used and given more prominence, and their functionality must be further considered within different lineups.

Practical applications and limitations

This study proposed a season-scale quantitative method of using lineups based on lineup networks. Some general patterns were found regarding the lineup composition of different levels of teams, which result in the following practical suggestions:

- (i) Too many peripheral lineups may harm the collective performance. Coaches can reduce the use of peripheral lineups by

summarizing the typical context where the peripheral lineups appear and coordinating substitution plans accordingly.

- (ii) Enhancing players' versatility and fostering chemistry among team members through intentional integration of diverse players into lineups during daily training or regular seasons allows coaches to gain deeper insights into individual players and their collective abilities.
- (iii) Players frequently featured in many connector lineups could be groomed as potential lead players for non-starter lineups.

There are some limitations of this study which should be acknowledged and further considered in future works. First, this study only focused on the playoff lineups and performance, which partly limits the representativeness of our conclusions. Second, the roles of lineups were identified by using only the topological network structure and playing time, while they could also be categorized according to their game statistics and the rival's information. Finally, the composition of lineups should be considered to understand the player roles within each lineup. The pipeline of this study can also be extended to other sports like football or handball, where the player groups can be extracted by finding communities from passing networks, based on which the connector players between communities could be found.

Conclusion

In summary, we adapted the lineup network to model the relationship between lineups in basketball and identified the lineup roles based on their patterns of inter- and intra-community connections as well as the playing time. The percentage of connector lineups showed a positive correlation with teams' standings, while the peripheral lineups were negatively correlated. The results regarding conserved rate also showed that the connector lineups were more used by strong teams during playoffs, demonstrating the importance of adding links between different lineups. These findings confirm the effectiveness of considering a community structure to explore the basketball lineup roles. Our research provides a quantitative tool to identify the roles of lineups and to optimize the lineup strategy and rotations.

CRediT authorship contribution statement

Tianxiao Guo: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Yixiong Cui:** Supervision, Conceptualization. **Christophe Ley:** Writing – review & editing, Supervision. **Wenjie Zhang:** Validation, Formal analysis, Data curation. **Yanfei Shen:** Supervision, Resources, Conceptualization. **Jing Mi:** Writing – review & editing, Supervision. **Chengyi Zhang:** Validation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

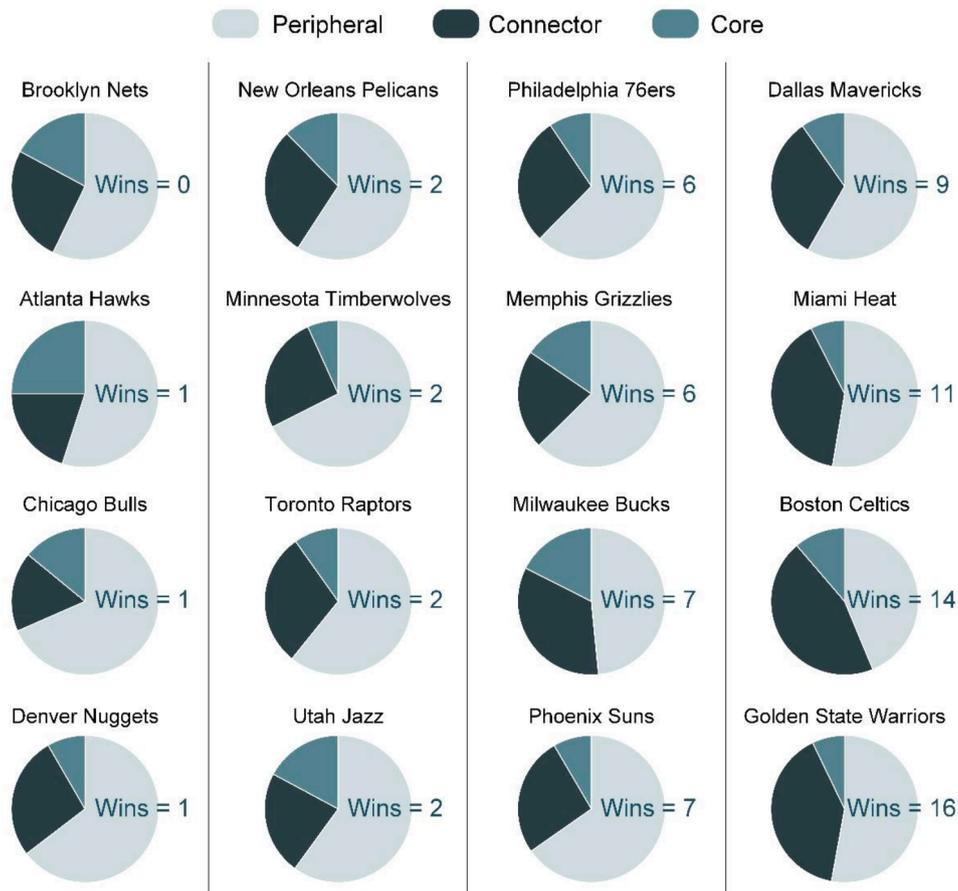


Fig. A1. Composition of the number of lineup types used by the 16 teams in the playoffs of the 2021–2022 NBA season.

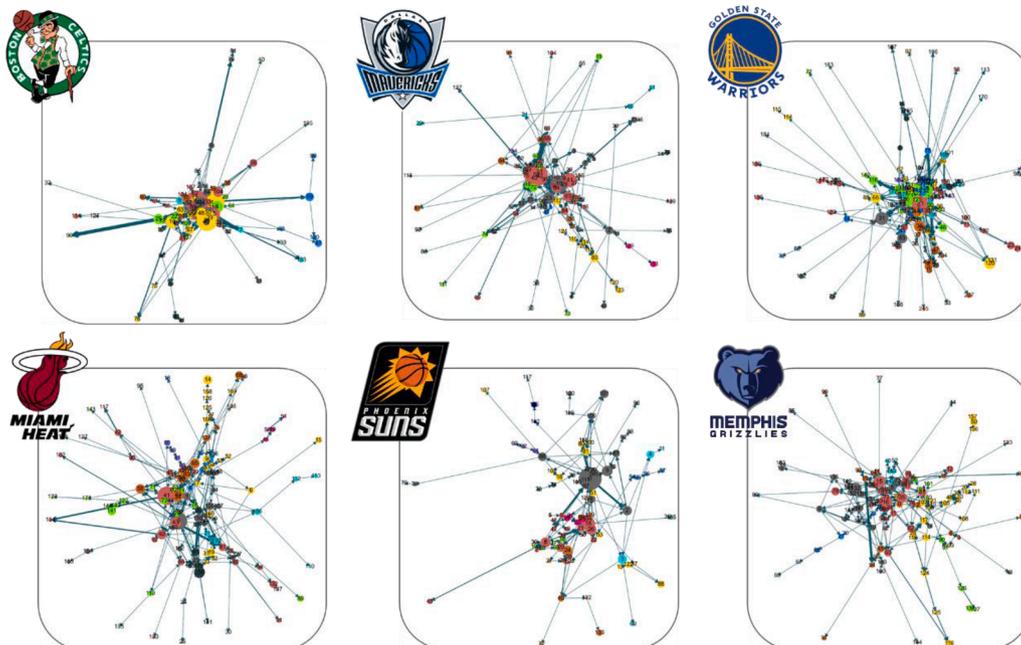


Fig. A2. Samples of constructed lineup substitution networks during 2021–22 season playoffs.

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