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Sports Science

Leicester City FC won the English Premier League: a network analysis of the team for the season 2015-2016

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Abstract - Aim: It is crucial to examine Leicester City FC's passing networks in the 2015-2016 English Premier League season as it provides detailed insights into player interactions within the team. **Methods:** Analysis of all 38 matches against 19 opponents, utilizing the OPTA database, revealed an average of 264.42 passes per game (SD = 72.65), totaling 10,048 passes between players. Gephi software (version 0.9.2) was employed to compute network metrics. One-way ANOVA was used to assess the influence of match location, performance, and opposition ranking on macro network metrics, as well as the influence of players' positions on micro network metrics. **Results:** Results demonstrated statistical differences between match locations and certain macro network metrics, indicating varying player interactions based on match locations and opposition levels. However, no statistical differences were found between team performance and examined macro network metrics, or between players' positions and micro network metrics. **Conclusion:** This study's main findings suggest that Leicester City FC exhibited distinct player interactions depending on match locations and the level of opposition during the season. Practical implications of these findings for coaching strategies or team performance analysis are worth exploring.

Keywords: network analysis, football, degree, diameter, density, clustering.

Introduction

Leicester City FC's astonishing victory in the 2015-2016 English Premier League season, defying 5,000/1 odds, has garnered significant media attention. Despite media attributions of success to lower possession (42.34, 18th EPL rank) and fewer passes (12,586, 18th EPL rank) against opponents[1], these analyses fall short of providing a comprehensive understanding of the team's season-long performance. Notably, scientific literature addressing the pivotal role of passing networks in their success is notably absent. This study seeks to fill this gap by delving into the intricacies of how the team interacted, both collectively and individually, against diverse opponents throughout the season. It not only contributes to sport performance literature but also offers insights relevant to Physical Education pedagogy, particularly in teaching team dynamics and tactical awareness[2].

The network analysis scrutinizes player interactions and records passes in a network diagram[3]. Players are represented as nodes corresponding to individuals in specific positions, and passes are depicted as edges signifying interactions between positions[4]. While these diagrams offer semi-quantitative insights into team passing networks, a more profound quantitative analysis is achievable through network mathematics techniques[5]. This approach allows for the identification of player interactions at the micro level and overall team passes at the macro level[6].

Micro-level analysis utilizes centrality measures such as In-Degree, Out-Degree, Closeness, and Betweenness Centrality[7] to discern player activity and connections within positional roles. The study identifies players well-connected with teammates (higher centrality) and those less connected (lower centrality). Notably, midfielders emerge as pivotal players[5,7]. Previous research on the FIFA World Cup 2014 demonstrated the centrality of midfielders in successful teams, emphasizing a specific attacking style employed by these teams[7].

Macro-level analysis examines team dynamics using network properties. The network diameter, representing the distance between players in a passing graph, quantifies the farthest distance between two players[5]. While statistical differences in diameter analysis were not found in a study of national soccer teams in the FIFA World Cup 2014, teams reaching the final stages and winning teams had the lowest mean values. Metrics such as density, measuring overall affection between teammates, and clustering coefficient, indicating interconnectivity, have shown differences between successful and unsuccessful teams[5,8].

In line with this, the present study has four primary goals: (1) to analyse potential differences based on match location (home/away) and team passing networks; (2) to compare passing networks according to team performance (win, draw, loss); (3) to analyse potential differences based on opponent rankings in the EPL (Champions League, Middle Table, Relegation) and team passing networks; (4) to identify the most prominent players in the team for each match and overall. Through these objectives, the study aims to unravel the intricacies of Leicester City FC's success by dissecting their passing networks across various dimensions, contributing to a more holistic understanding of their exceptional achievement.

Methods

Sample

A comprehensive analysis was conducted on all 38 matches played by Leicester City FC during the English Premier League season 2015-2016. These matches encompassed both home and away fixtures, involving encounters with all 19 opponents participating in the league that season. The dataset includes an average of 264.42 passes per game (SD = 72.65), resulting in a cumulative total of 10,048 passes exchanged between players. The passing statistics exhibit variation across individual matches, with the highest number of passes recorded in a single game being 431 during a home match against West Bromwich Albion. In contrast, the lowest number of passes occurred in a match played away against Manchester United, with a minimum of 161 passes. This wide range in passing frequencies underscores the dynamic nature of Leicester City FC's gameplay throughout the season.

Data collecting and processing

All the matches played by Leicester City FC during the English Premier League season 2015-2016 were sourced from the OPTA database. The players from Leicester City FC were identified using unique numerical codes assigned by the database (e.g., 78412), initially organized in a separate Excel sheet. Subsequently, these numerical codes were substituted with the corresponding players' names (e.g., Okazaki) through the utilization of the lookup tables function. To explore the connections within the team, the passes between players were delineated. Each match ID (e.g., 803167) was associated with two team IDs (away and home). For instance, away team ID 8 represented Sunderland, and home team ID 13 represented Leicester. Passes (Type ID 1) made by each Leicester City player during a match were recorded under the respective team IDs. Notably, passes involving more than one Leicester City player (Team ID 13) were considered successful passes for the given sequence. The sequence concluded when a player from the opposition team (e.g., Team ID 8) was subsequently listed in the database. The connections established for analysis are based on the players, represented as nodes, and the passes between them, denoted as edges in network terminology. Each pass between players was coded as one, with multiple passes codified with the corresponding numerical value indicating the number of passes involved in the sequence. This systematic approach provides a robust foundation for examining the passing networks of Leicester City FC, offering valuable insights into the interactions and connections between individual players throughout the season.

Network analysis

In the analysis of the 38 datasets derived from the social network analysis of Leicester City FC, a set of network metrics was computed utilizing the Gephi software (version 0.9.2). This software was employed not only for metric computation but also for the visual representation of the passing networks. The focus in this analysis was on completed passes executed by players within the team.

Macro-level analysis was employed to scrutinize the team using network properties[5,8]. The network diameter, indicating the distance between players in a passing graph measured in the number of links, was considered. The density metric, assessing the overall interaction intensity among teammates, and the clustering coefficient, gauging the interconnectivity in the proximity of a player, were also integral components of the analysis.

Micro-level analysis, in the form of centrality measures, was implemented to discern the activity of each player or set of players within their positional roles[5,9]. Specifically, these micro-level analyses were employed as centrality measures to identify players who were well-connected and those less connected with their teammates. In-Degree Centrality pinpointed players who received more passes, while Out-Degree Centrality highlighted those utilizing more passes to their teammates. Closeness Centrality was employed to identify the most straightforward route to reach a specific player within the team, while Betweenness Centrality illuminated how the ball flowed between players' positions contingent on their location[9]. These micro-level centrality measures offer a nuanced understanding of player dynamics and interactions within Leicester City FC's passing networks.

Statistical procedures

The impact of match location, match performance, and opposition ranking on macro network metrics, as well as the influence of players' positions on micro network metrics, was assessed through one-way ANOVA. Assumptions of normality and homogeneity were scrutinized using Kolmogorov-Smirnov tests ($p > 0.05$) and Levene's test ($p > 0.05$), respectively[10]. In instances where significant statistical differences emerged among the factors, Tukey's HSD post-hoc test was employed for further examination (Maroco, 2012). To quantify effect size, the following scales based on Hopkins, Hopkins, and Glass

(1996) were applied: very small (0-0.01), small (0.01-0.09), moderate (0.09-0.25), large (0.25-0.49), very large (0.49-0.81), and nearly perfect (0.81-1.0). All statistical analyses were conducted using IBM SPSS Statistics (version 27) with a predefined significance level of $p < 0.05$.

Results

The results of the study shed light on the intricate dynamics of Leicester City FC's interactions with their teammates during ball possession. The analysis delves into potential network variations in the team's gameplay against all English Premier League opponents, discerning both macro and micro levels of analysis. The factors under consideration include match location, performance, opponents' ranking, and players' positions. This comprehensive examination provides valuable insights into how Leicester City FC's passing networks vary across different scenarios and opponents. The findings contribute to a nuanced understanding of the team's strategic approach, highlighting the impact of both contextual and individual factors on their overall performance during the 2015-2016 English Premier League season.

Macro levels of analysis

To access potential differences between the location of the match and the macro network features of the teams, an ANOVA test was performed. The results are presented in Table 1.

Statistical differences were found between the location of the match features of the teams and the Weighted Indegree ($F_{1,37} = 4.456$; $p = 0.042$; $\eta_p^2 = 0.11$; moderate effect size), Weighted Outdegree ($F_{1,37} = 4.456$; $p = 0.042$; $\eta_p^2 = 0.11$; moderate effect size), Weighted Degree ($F_{1,37} = 4.456$; $p = 0.042$; $\eta_p^2 = 0.11$; moderate effect size), Average Weighted Degree ($F_{1,37} = 5.171$; $p = 0.029$; $\eta_p^2 = 0.126$; moderate effect size), Network Diameter ($F_{1,37} = 5.444$; $p = 0.025$; $\eta_p^2 = 0.131$; moderate effect size), Network Density ($F_{1,37} = 6.801$; $p = 0.013$; $\eta_p^2 = 0.159$; moderate effect size). No differences were found in the Clustering Coefficient ($F_{1,37} = 1.713$; $p = 0.199$; $\eta_p^2 = 0.045$; small effect size). All the metrics means are higher for the Home location compared to the Away location, apart from the Network Diameter, which is the opposite.

These results suggest that the team's passing networks exhibit variations depending on the match location, with certain metrics showing higher values when playing at home. The differences in Network Diameter, where the values are higher for Away location, add an interesting dimension to the analysis. It implies that although the overall passing networks may be denser at home, there might be longer passing sequences or connections when playing away.

To assess potential differences between the performance of the team and the macro network features of the teams, an ANOVA test was performed. The results are presented in Table 2.

No statistical differences were found between the team performance and the Weighted Indegree ($F_{2,37} = 0.093$; $p = 0.912$; $\eta_p^2 = 0.005$; very small effect size), Weighted Outdegree ($F_{2,37} = 0.093$; $p = 0.912$; $\eta_p^2 = 0.005$; very small effect size), Weighted Degree ($F_{2,37} = 0.093$; $p = 0.912$; $\eta_p^2 = 0.005$; very small effect size), Average Weighted Degree ($F_{2,37} = 0.084$; $p = 0.92$;

Table 1 - Descriptive table (mean and standard deviation) and statistical comparison between factors (location of the match).

		Weighted indegree	Weighted outdegree	Weighted degree	Ave weighted degree	Diameter	Density	Clustering coefficient
Home	AVE	288.21	288.21	576.42	21.20	2.53	0.59	0.68
	STD	73.94	73.94	147.88	5.29	0.51	0.05	0.05
Away	AVE	240.63	240.63	481.26	17.48	2.89	0.54	0.65
	STD	64.70	64.70	129.41	4.77	0.46	0.07	0.07

Table 2 - Descriptive table (mean and standard deviation) and statistical comparison between factors (performance).

		Weighted indegree	Weighted outdegree	Weighted degree	AVE weighted degree	Diameter	Density	Clustering coefficient
Win	AVE	268.52	268.52	537.04	19.74	2.74	0.56	0.67
	STD	64.45	64.45	128.91	4.95	0.54	0.07	0.06
Draw	AVE	267.50	267.50	535.00	19.47	2.67	0.58	0.67
	STD	88.58	88.58	177.16	6.05	0.49	0.07	0.07
Loss	AVE	220.67	220.67	441.33	15.76	2.67	0.50	0.62
	STD	75.25	75.25	150.50	5.38	0.58	0.09	0.05

η_p^2 = 0.005; very small effect size), Network Diameter ($F_{2,37}$ = 0.063; p = 0.939; η_p^2 = 0.004; very small effect size), Network Density ($F_{2,37}$ = 0.642; p = 0.532; η_p^2 = 0.035; small effect size), and Clustering Coefficient ($F_{2,37}$ = 0.524; p = 0.597; η_p^2 = 0.029; small effect size).

To access potential differences between the ranking of the opponent teams and the macro network features of the teams, an ANOVA test was performed. The results are presented in Table 3.

Statistical differences were found between the ranking of the opponent teams features of the teams and the Weighted Indegree ($F_{2,37}$ = 4.165; p = 0.024; η_p^2 = 0.192; moderate effect size), Weighted Outdegree ($F_{2,37}$ = 4.165; p = 0.024; η_p^2 = 0.192; moderate effect size), Weighted Degree ($F_{2,37}$ = 4.165; p = 0.024; η_p^2 = 0.192; moderate effect size), and Average Weighted Degree ($F_{2,37}$ = 3.923; p = 0.029; η_p^2 = 0.183; moderate effect size). No differences were found in the Network Diameter ($F_{2,37}$ = 0.905; p = 0.414; η_p^2 = 0.049; small effect size), Network Density ($F_{2,37}$ = 0.971; p = 0.388; η_p^2 = 0.053; small effect size), and Clustering Coefficient ($F_{2,37}$ = 1.313; p = 0.282; η_p^2 = 0.07; small effect size). All the metrics means are higher for the matches against opponents ranked at the relegation places compared with the middle table places, champions league places, apart from the Network Diameter, which is the opposite.

Micro levels of analysis

Table 4 includes all the players from the Leicester City Team, their positions and network metrics for each player.

To access potential differences between the players' positions and the micro network features, an ANOVA test was performed. The results are presented in Figure 1. A higher Weighted Degree was found for Drinkwater (Midfielder), Kante (Midfielder), and Fuchs (Defender); and a lower Weighted Degree was found for Doddo (Forward), James (Midfielder), and Benalouane (Defender).

No statistical differences were found between the players positions and the Weighted Indegree ($F_{2,21}$ = 0.222; p = 0.803; η_p^2 = 0.023; small effect size), Weighted Outdegree ($F_{2,21}$ = 0.361; p = 0.702; η_p^2 = 0.043; small effect size), Weighted Degree ($F_{2,21}$ = 0.246; p = 0.784; η_p^2 = 0.027; small effect size).

The results on Closeness Centrality for all players can be found in Figure 2. The higher Closeness Centrality was found for Schmeichel (Goalkeeper), Kante (Midfielder), and Okazaki (Forward). The lower Closeness Centrality was found for Doddo Forwardd), James (Midfielder), and Benalouane (Defender). No statistical differences were found between the players positions and the Closeness Centrality ($F2,21$ = 0.079; p = 0.924; ηp^2 = 0.083; small effect size). The results on Betweenness Centrality for all players can be found in Figure 3. The higher Betweenness Centrality was found for Kante (Midfielder), Okazaki (Forward), and King (Midfielder). The lower Betweenness Centrality was found for Wasilewski (Defender), Gray (Midfielder), and James (Midfielder). No statistical differences were found between the players positions and Betweenness Centrality ($F2,21$ = 0.304; p = 0.741; ηp^2 = 0.08; small effect size).

Discussion

The examination of player interactions within a team offers crucial insights into ball possession dynamics and playing strategies[11,12,13]. Applying network metrics enables the identification of team-wide characteristics (macro levels of analysis) and individual player contributions based on their positions[5]. This study utilizes network analysis metrics to elucidate the passing networks of Leicester FC in the English Premier League during the 2015-2016 season and identifies key players and positions influencing the attacking process in the league.

The results underscored statistical disparities between match locations and certain analysed macro network metrics (Weighted Indegree, Weighted Degree, Average Weighted Degree, Network Diameter, and Network Density). Notably, all metric means were higher for Home matches compared to Away matches, except for Network Diameter, which exhibited the opposite trend. These findings affirm that teams exhibit distinct playing styles at home and away, with higher passing networks observed in home matches. This aligns with earlier research[14], indicating that home teams tend to show

Table 3 - Descriptive table (mean and standard deviation) and statistical comparison between factors (Ranking).

		Weighted indegree	Weighted outdegree	Weighted degree	AVE weighted degree	Diameter	Density	Clustering coefficient
Champions League	AVE	208.00	208.00	416.00	15.28	2.88	0.54	0.64
	STD	46.37	46.37	92.74	3.37	0.35	0.07	0.04
Middle Table	AVE	272.83	272.83	545.67	19.97	2.71	0.57	0.67
	STD	70.28	70.28	140.57	5.09	0.55	0.07	0.07
Relegation	AVE	306.00	306.00	612.00	22.21	2.50	0.58	0.68
	STD	76.24	76.24	152.47	5.95	0.55	0.08	0.06

Table 4 - Players' positions and network metrics for the players.

Position	Name	Weighted indegree	Weighted outdegree	Weighted degree	Closeness centrality	Betweenness centrality
Goalkeeper	Schmeichel	459	591	1050	0.95	13.22
Defender	Huth	398	581	979	0.84	1.39
Defender	Morgan	487	631	1118	0.88	6.19
Defender	de Laet	195	209	404	0.81	11.04
Defender	Fuchs	974	1024	1998	0.88	5.77
Defender	Benalouane	9	10	19	0.59	1.97
Defender	Simpson	706	818	1524	0.84	3.48
Defender	Wasilewski	41	50	91	0.70	0.07
Midfielder	King	348	377	725	0.91	15.32
Midfielder	Drinkwater	1530	1474	3004	0.88	4.40
Midfielder	Mahrez	941	789	1730	0.91	9.10
Midfielder	Schlupp	424	394	818	0.84	3.60
Midfielder	Albrighton	930	659	1589	0.88	6.34
Midfielder	Kante	979	1084	2063	0.95	27.68
Midfielder	Inler	82	100	182	0.73	0.21
Midfielder	Dyer	55	49	104	0.75	3.21
Midfielder	James	10	9	19	0.56	0.12
Midfielder	Gray	80	70	150	0.66	0.07
Midfielder	Amartey	53	59	112	0.68	0.14
Forward	Okazaki	431	387	818	0.91	16.13
Forward	Vardy	564	400	964	0.84	5.46
Forward	Dodoo	4	3	7	0.53	0.14
Forward	Ulloa	348	280	628	0.78	7.82

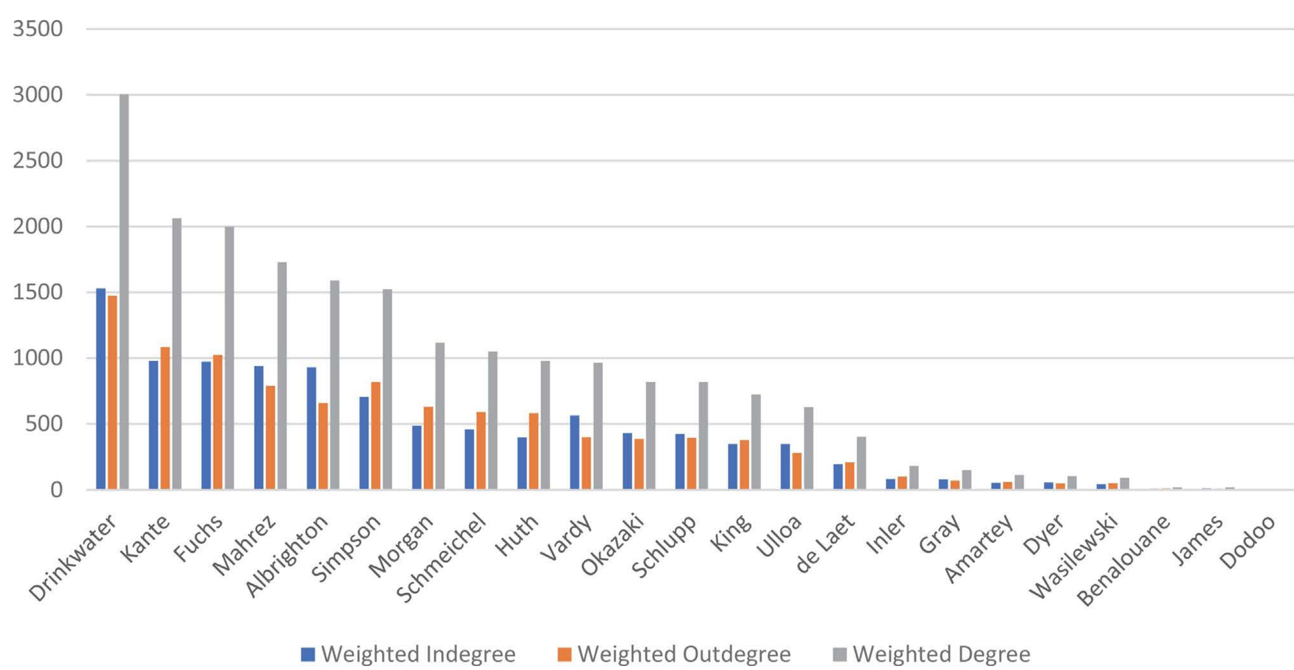

Figure 1 - Weighted Degree metrics for all Leicester City FC matches from all players of the team.

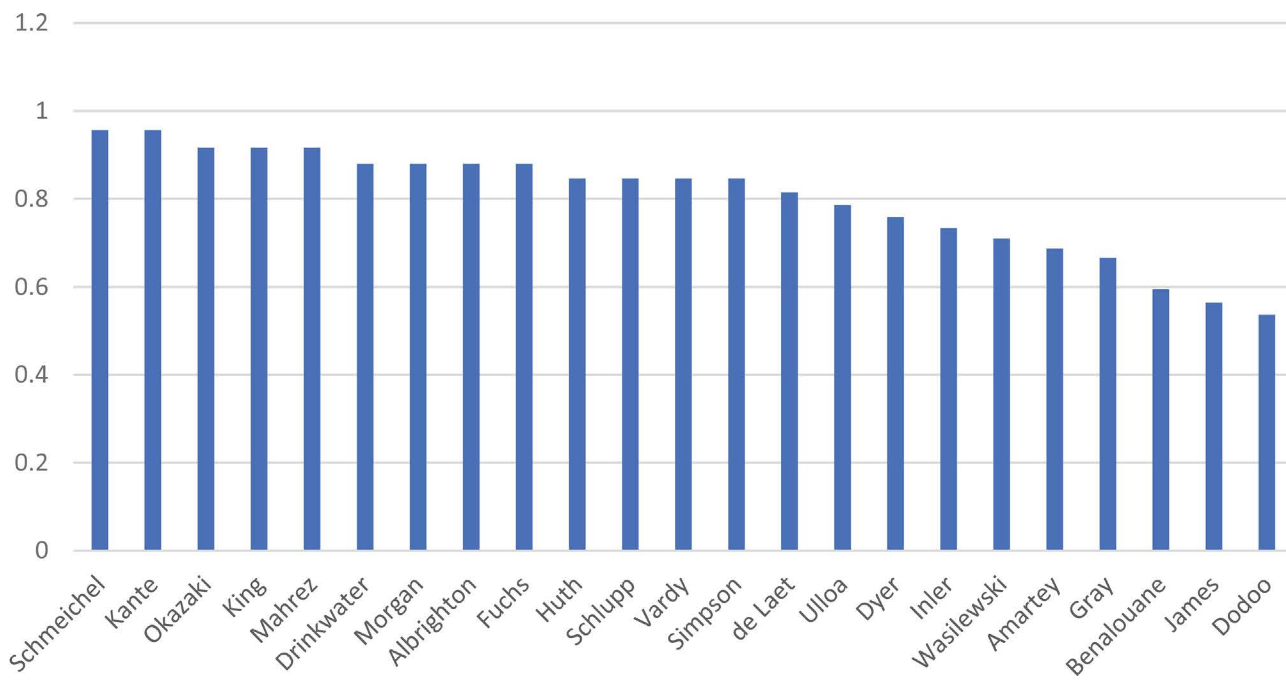

Figure 2 - Closeness Centrality metrics for all Leicester City FC matches from all players of the team.

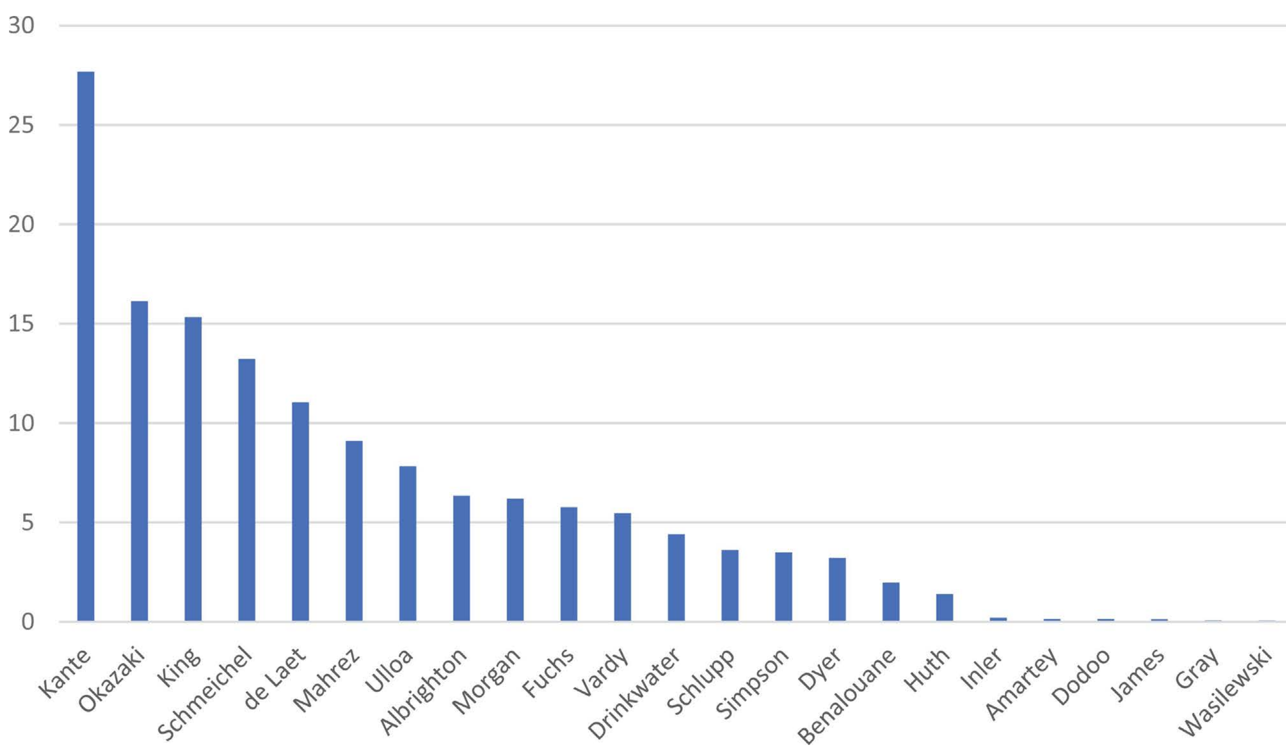

Figure 3 - Betweenness Centrality metrics for all Leicester City FC matches from all players of the team.

superior attack indicators, including passes, successful passes, and ball possession.

No statistical differences emerged between team performance and the examined macro network metrics. This aligns with previous studies that found no statistical distinctions in clustering coefficient and network diameter, although differences were observed in network density[8]. In contrast, significant differences were identified between opponent team rankings and Weighted Indegree, Weighted Outdegree, Weighted Degree, and Average Weighted

Degree. The mean values for these metrics were higher for matches against relegation-ranked opponents compared to middle table and champions league-ranked opponents, with Network Diameter showing the opposite trend. Comparable studies on the FIFA World Cup 2010 also found that higher-ranked teams executed more passes per match[13], reinforcing the importance of team ranking in passing interactions.

Examining micro network metrics revealed higher Weighted Degree for players in Midfielder and Defender positions, distributed Closeness Centrality for Goalkeeper, Midfielder, and Forward positions, and higher Betweenness Centrality for players in Midfielder and Forward positions. However, no statistical differences were found between players' positions and these metrics. Previous studies have consistently shown that midfielders tend to exhibit the highest levels of Closeness Centrality and Betweenness Centrality[9,15], attributed to their involvement in executing passes during the attacking phase to prepare for goal-scoring opportunities.

While this study contributes valuable insights into Leicester City FC's passing networks during the 2015-2016 season, certain limitations should be acknowledged. Notably, the study did not analyse opponent networks, which could provide a more comprehensive understanding. Future research should consider examining opponents, especially those with varying ranking levels, to compare passing networks effectively. Additionally, not comparing network metrics with team formations or different attacking phases represents another limitation. Future studies should incorporate these factors to offer more nuanced information for practical applications. Practically, this study can aid coaches and performance analysts in understanding how underrated teams perform in terms of ball possession, facilitating informed decision-making when working with similar teams.

The significance of passing interactions in elite football extends beyond tactical execution. They represent structured, learnable patterns of cooperation that align with pedagogical models in Physical Education, particularly those emphasizing ecological dynamics[2]. In the context of the English Premier League and comparable continental competitions, passing networks have become a foundation of performance analysis[16]. Following Leicester City FC's 2015-2016 season, clubs have adopted or refined network-based metrics to evaluate team cohesion and player influence within different formations. These metrics are now integrated into coaching curricula, scouting protocols, and match preparation routines, reflecting a broader shift toward data-informed pedagogy in sport. For Physical Education practitioners, these metrics offer an opportunity to teach cooperation, spatial awareness, and decision-making, bridging elite performance analysis with educational practice.

Leicester City's tactical evolution following their 2015-2016 title win reflects both the influence and limitations of their original network model. Under Claudio Ranieri, the team thrived on compact defensive structures and rapid transitional play, supported by lean passing networks. However, in subsequent seasons, Leicester adopted more possession-oriented systems, emphasizing build-up play and positional rotations. This shift mirrored broader trends in European football, where clubs increasingly integrated multilayered network dynamics to balance control and creativity. While Leicester's initial model was not universally replicated, it catalyzed a rethinking of tactical diversity, showing that success could emerge from efficient, context-sensitive interaction patterns rather than dominant possession metrics. For educators and analysts, this trajectory underscores the importance of adaptability and contextual learning in team sports.

Leicester City's passing network patterns in the 2015-2016 season were distinct from dominant paradigms in elite football, which typically emphasized high-possession, short-passing styles. Instead, Leicester's success was built on more direct passing structures that prioritized efficiency and transitional play. These standards, characterized by lower overall possession but strategically concentrated interactions, challenged prevailing assumptions about ball control and spatial dominance. In subsequent seasons, clubs have incorporated similar principles, blending compact network structures with high pressing and rapid transitions. While not universally replicated, Leicester's model demonstrated that alternative network configurations could yield competitive success, prompting broader tactical experimentation across major competitions.

Conclusion

The key findings of this study highlight that Leicester City FC exhibits elevated macro network metrics in home matches compared to away matches, and in matches against opponents ranked at relegation places compared to those in middle table and champions league places. These results suggest that the team's interactions among players vary based on match location and the caliber of the opposition throughout the season. Additionally, while the micro network metrics analysed imply a certain prominence for the midfielder position, it is noteworthy that no statistical differences were found to substantiate this observation. These findings also hold pedagogical value for Physical Education, where understanding interaction patterns can inform instructional strategies that emphasise cooperation, spatial reasoning, and adaptive decision-making.

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