Network analysis of offensive dynamics in a Portuguese First Division football team: insights from the 2020-2021 season

Análisis de redes y dinámicas ofensivas de un equipo de fútbol de la primera división portuguesa: perspectivas de la temporada 2020-2021

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Abstract

Introduction: Network analysis has gained increasing attention, as it provides a framework for identifying both collective and individual behaviours within the football teams.
Objective: This study aimed to analyse the offensive actions that resulted in shots using network analysis in a Portuguese First Division football team during the 2020-2021 season.
Methodology: All 34 matches were coded using Angles® software. Offensive actions were defined as sequences starting with a ball recovery and ending with a shot. Adjacency matrices were constructed for each match, and both macro and micro analytical approaches were employed to examine differences between the two halves of the season.
Results: Findings indicated 914 intra-team interactions, with player 14 (midfielder) and player 2 (forward) as key contributors, particularly in micro network metrics such as degree prestige (passes received) and degree centrality (passes made). Statistical analysis revealed no significant differences in network metrics, including density ($W = 95$, $p = 0.0912$) and clustering coefficient ($W = 112$, $p = 0.2689$), between the season halves.
Discussion: These findings offer valuable insights for practitioners seeking in recognizing play patterns and optimizing team dynamics. Identifying key players allows coaches to design targeted training exercises, enhance player roles, and better assess opposition threats and vulnerabilities.
Conclusions: Network metrics provides a comprehensive understanding of team dynamics, particularly in identifying key contributors to offensive actions.

Keywords

Match analysis; network analysis; performance metrics; team dynamics.

Resumen

Introducción: El análisis de redes ha ganado cada vez más atención, ya que proporciona un marco para identificar tanto los comportamientos colectivos como individuales dentro de los equipos de fútbol.
Objetivo Este estudio tuvo como objetivo analizar las acciones ofensivas que resultaron en tiros utilizando el análisis de redes en un equipo de la Primera División portuguesa durante la temporada 2020-2021.
Metodología: Se codificaron los 34 partidos utilizando el software Angles®. Las acciones ofensivas se definieron como secuencias que comenzaban con una recuperación de balón y terminaban con un tiro. Se construyeron matrices de adyacencia para cada partido y se emplearon enfoques analíticos tanto macro como micro para examinar las diferencias entre las dos mitades de la temporada.
Resultados: El análisis identificó 914 interacciones dentro del equipo, con el jugador 14 (centrocampista) y el jugador 2 (delantero) como los principales contribuyentes, especialmente en las métricas de redes a nivel micro, como el prestigio de grado (pases recibidos) y la centralidad de grado (pases realizados). El análisis estadístico no reveló diferencias significativas en las métricas de redes, incluyendo la densidad ($W = 95$, $p = 0.0912$) y el coeficiente de agrupamiento ($W = 112$, $p = 0.2689$), entre las mitades de la temporada.
Discusión: Estos hallazgos proporcionan información valiosa para los profesionales que buscan reconocer patrones de juego y optimizar la dinámica del equipo. Identificar a los jugadores clave permite a los entrenadores diseñar ejercicios de entrenamiento específicos, mejorar los roles individuales y evaluar mejor las amenazas y vulnerabilidades del equipo contrario.
Conclusiones: Las métricas de redes ofrecen una comprensión integral de la dinámica del equipo, particularmente en la identificación de los jugadores clave en las acciones ofensivas.

Palabras clave

Análisis de partidos; análisis de redes; dinámicas de equipo; métricas de rendimiento .

Introduction

Match analysis in football has become an increasingly attractive field of study, particularly with the integration of new technologies such as video and data analysis software. These advancements have provided coaches and analysts with extensive information to analyse both their own teams and their opponents. The exponential growth of available data has necessitated the involvement of highly qualified professionals, leading to the emergence of new roles in football teams, such as video analysts, data analysts, and data scientist (Mehta et al., 2024). This influx of data has resulted in the development of new metrics to evaluate team performance during competitions, offering coaches and analysts deeper insights into team dynamics and performance (Mehta et al., 2024; Pueyo Romeo et al., 2024).

Among the most studied aspects of match analysis are the collective and individual behaviours of teams. Analysts and researchers often use performance variables to generate actionable information for coaches and technical staff (Clemente, 2018). In recent years, network analysis of team passing distribution has gained increasing attention, as it provides a framework for identifying both collective and individual behaviours within the team (Buldú et al., 2018; Pacheco et al., 2022).

Player passing networks can be constructed by mapping connections between players during ball possession sequences, where players are represented as nodes and passes as links. By analysing specific network metrics, it is possible to evaluate a team's global performance and the individual contributions of each player. For example, a study of 64 matches during the 2018 FIFA World Cup found that winning teams tend to exhibit higher values in global metrics such as team density, clustering coefficient, and total arcs (Clemente, 2018). Similarly, an analysis of 12 matches from the UEFA Champions League indicated that network density can serve as a predictor of a team's success in creating goal opportunities (Pina et al., 2017). However, the results of these metrics can vary depending on the type of analysis conducted (Alves et al., 2022).

On a micro level, a study of the French First Division analysed which players contributed most to their team's dynamics. It concluded that defensive midfielders, box-to-box midfielders, and central defenders were the most prominent players (Sarmento et al., 2020). Similarly, another study found that midfielders were typically the most relevant players in their teams' offensive actions (Reigal et al., 2024).

All this information can help coaches and analysts gain in-depth understanding of whether a team is cohesive, evaluate the opponent's cohesion, and identify which players influence team dynamics. Higher values in the density metric can present a more possession style used by teams (Pan et al., 2024). This can validate the initial video analysis conducted by coaches and analyst regarding how the opponent team plays and highlight which players are the most important within a given team (Alves et al., 2022; Caicedo-Parada et al., 2020). Also, this information can assist coaches in creating game plans and strategies to disrupt the opponent's team dynamics, as well as inform their own players about which opponent players need to be closely marked to stop their contribution in their team dynamics (Arriaza-Ardiles et al., 2018; Caicedo-Parada et al., 2020).

While many studies have focused on team performance in relation to match status or tactical systems (Aquino et al., 2019), there is a notable gap in research that examines team performance across different halves of a season. This is an important area of study, as team performance throughout a season can be influenced by various factors. By utilising specific metrics, it becomes possible to identify reasons for performance fluctuations, which may help coaches address issues they had not previously considered.

In view of the above, this study aimed to analyse the offensive actions that resulted in shots during the 2020-2021 season of the Portuguese First Division. The analysis is twofold: i) to determine if there were differences in network macro metrics (density and clustering coefficient) between the first and second halves of the season, and ii) to identify which players contributed most to the team's offensive dynamics using micro network metrics (degree centrality and degree prestige). It is hypothesised that there will be significant differences in the network macro metrics (density and clustering coefficient) between the first and second halves of the 2020-2021 season in the Portuguese First Division. As well, it is expected that certain players, specifically midfielders and forwards, will exhibit higher values in network micro metrics (degree centrality and degree prestige), indicating their greater contribution to offensive actions that lead to shots (Reigal et al., 2024; Sarmento et al., 2020).

Method

Sample

We analysed 34 matches from a professional football team competing in the Portuguese First Division during the 2020-2021 season. The study focused on a complete season which included a balanced mix of home and away games across various levels of competition, ensuring a representative sample of the team's performance. A total of 914 intra-team interactions were recorded and analysed, which encompassed passing sequences, ball recoveries, and other offensive actions that led to shots. This sample size was strategically chosen to provide a comprehensive overview of the team's tactical behaviour throughout the season (Pina et al., 2017). The team had limited prior appearances in the first division, primarily aiming to retain their league status over the years. Notably, during the season under review, the team achieved one of their best performances, securing a position in the upper half of the league table among eighteen competing teams.

The video footage for all matches was retrieved from the Wyscout© platform, supplemented by tactical footage provided by the club's analyst, ensuring a high level of detail in the analysis (Alves et al., 2022). To maintain the consistency and accuracy of the data, all footage was reviewed by trained analysts, and the coding of events was cross verified using Angles® analysis software.

All procedures followed the ethical standards outlined in the Declaration of Helsinki. The study received approval from the Ethics Committee of the Faculty of Sports Sciences and Physical Education at the University of Coimbra. Measures regarding the Pass Executor and Pass Receiver were taken to anonymise player data and ensure that personal information was protected throughout the study.

Procedures

After obtaining access to the video footage, all 34 matches were meticulously coded using Angles® software, developed by Fulcrum Technologies®. A customised coding window was created to extract the necessary data for analysis. Three variables were created in the code window (ball recovery, pass and shot) along with location of the pitch where the action occurred and the player who did it. Offensive actions were defined as sequences starting with a ball recovery by the team and ending with a shot. Each event within these sequences (e.g., ball recoveries, passes, receptions, crosses, shots) was accurately recorded and mapped to specific locations on the football pitch. For each pass, both the starting and ending locations were documented, and the outcome of every shot was classified as goal, off target, blocked, saved, or hitting the post. Additionally, the players involved in each action were identified and coded accordingly (Alves et al., 2022).

To further categorise the offensive actions, it was classified each sequence by type of play: open play, transition play, and set play. Cartesian coordinates were used to pinpoint the exact locations of ball recoveries, passes, and shots, enabling a precise spatial analysis of the events. This detailed coding allowed to construct adjacency matrices for each match, which were subsequently analysed using RStudio. For the network analysis, it was employed both macro and micro analytical approaches. At the macro level, it was analysed global team properties, focusing on two key metrics: density and clustering coefficient. Density represents the ratio of observed links to the maximum possible links in the network, with values ranging from 0 (no connectivity) to 1 (maximal cooperation). The clustering coefficient measures the degree of interconnectedness among close teammates, similarly, ranging from 0 to 1, reflecting the level of cooperation within subgroups of the team (Praça et al., 2019; Ribeiro et al., 2017).

At the micro level, it was assessed player-specific contributions using three centrality measures: i) Degree centrality (out-degree), which represents the total number of passes made by a player, indicating their involvement in offensive play; ii) Degree prestige (in-degree), which measures the number of passes received by a player, reflecting their prominence as a target for teammates (Praça et al., 2019; Ribeiro et al., 2017).

The independent variable for the analysis was the half of the season, which was divided into two categories: the first half and the second half, with 17 matches analysed in each period for a total of 34 matches.

Data analysis

The raw data was exported and processed for statistical analysis using RStudio (version 2023.06.1). The primary objective of the analysis was to determine whether there were significant differences in team network metrics—specifically density and clustering coefficient—between the first and second halves of the season. For this purpose, it was compared the first 17 matches (first half of the season) with the second 17 matches (second half of the season) of the Portuguese Championship during the 2020-2021 season.

Intra-observer reliability for the variables "Pass Executor" and "Pass Receiver" was assessed using Cohen's Kappa coefficient via IBM SPSS software (version 29). To evaluate intra-observer consistency, a subset representing 10% of the total sample was reanalysed, as suggested in prior research (O'Donoghue, 2009; Coutinho et al., 2024). The Kappa values were categorized as follows: values ranging from 0.81 to 1.0 indicated very good reliability; 0.61 to 0.80 were considered good; 0.41 to 0.60 denoted moderate reliability; 0.21 to 0.40 were viewed as fair; and values below 0.21 were classified as poor. In this analysis, the Kappa values achieved were 0.99 for both the "Pass Executor" and "Pass Receiver" variables, denoting exceptionally high reliability, aligning with findings from other studies (Coutinho et al., 2024).

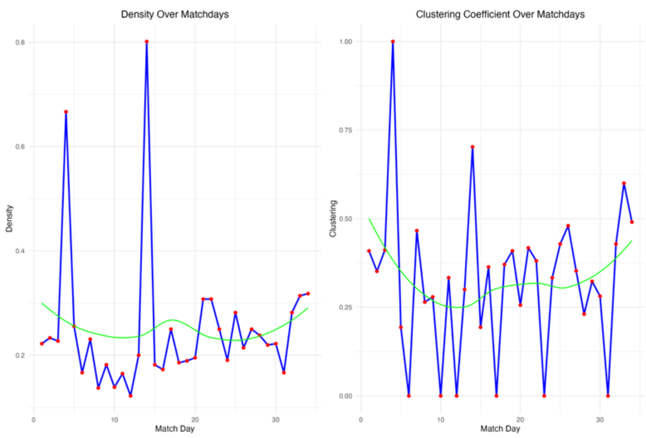
To assess the distribution of the data, it was first applied the Shapiro-Wilk test to test for normality. Results indicated that the density and clustering coefficient metrics did not follow a normal distribution. Consequently, it was employed the Mann-Whitney U test, a non-parametric alternative to the t-test, to evaluate differences in these metrics between the two halves of the season. This test was chosen due to its suitability for non-normally distributed data and its ability to compare two independent groups.

The Mann-Whitney U test allowed to examine whether any statistically significant differences existed in the density and clustering coefficient values between the first and second halves, thereby providing insights into the consistency of the team's network dynamics throughout the season.

Results

The analysis revealed no statistically significant differences in the network metrics between the first and second halves of the season. For the density metric, the Mann-Whitney U test indicated no significant difference ($W = 95$, $p = 0.0912$). Similarly, for the clustering coefficient, the results showed no significant difference between the two halves ($W = 112$, $p = 0.2689$) (Figure 1).

Figure 1. Density and Clustering Coefficient metrics variations over matchdays.



In total, 1,536 events were recorded across the season, which were categorised into three types: ball recovery, pass, and shot. Table 1 provides a breakdown of these events. A greater number of actions occurred during transition play (n=142) compared to open play (n=97) and set play (n=72). When the data was divided by season halves, the first half showed a total of 749 events (148 actions), with 51 open plays, 42 set plays, and 55 transition actions. In contrast, the second half registered 787 events (163 actions), with 46 open plays, 30 set plays, and 87 transition actions.

Table 1. Total number of events coded during the season.

Event Name	Total
Ball Recovery	311
Pass	914
Shot	311

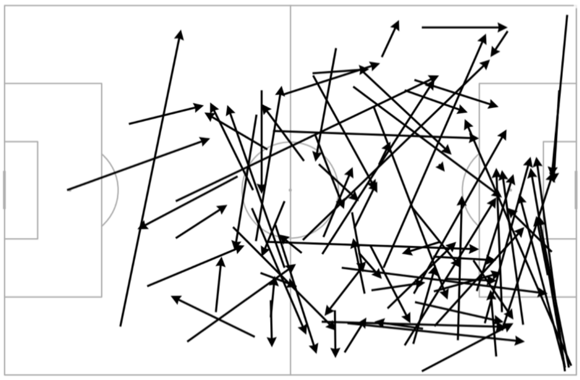
From a global perspective, the team's average density across the entire season was 0.571. When broken down by halves, the first half presented an average density of 0.401, while the second half showed a slight increase to 0.442. Regarding the clustering coefficient, the season average was 0.664, with the first half recording 0.421 and the second half showing a decline to 0.335. The team network matrix revealed that a total of 914 interactions (passes) occurred in the offensive actions that ended in a shot (Table 2).

Table 2. Example of data structure of interactions established between players during the offensive actions that ended in finishing.

Player	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
1	0	3	0	0	4	0	1	5	3	0	0	1	1	2	2	1	0	4	0	0	1	0	0	4	32
2	1	0	5	1	4	1	5	5	5	7	0	3	2	14	2	6	0	7	2	4	1	2	0	0	77
3	1	1	0	0	1	1	0	0	2	4	0	0	0	1	0	1	1	1	3	0	0	1	1	2	21
4	0	1	1	0	1	0	3	1	0	0	1	3	0	3	0	0	0	0	1	0	2	0	0	2	19
5	0	3	1	1	0	0	7	2	8	5	0	4	0	5	2	3	0	3	2	0	1	0	0	3	50
6	1	0	1	1	1	0	0	0	0	1	0	2	0	0	1	0	1	1	0	0	0	0	0	2	12
7	1	7	1	2	4	0	0	3	1	7	0	3	1	7	1	7	1	1	4	2	1	1	0	1	56
14	4	14	2	3	6	0	5	3	5	6	0	5	0	0	1	16	0	8	1	1	1	5	0	3	89
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Total Received	32	85	24	22	51	5	79	41	58	52	3	49	12	73	22	77	15	66	36	12	20	18	4	58	914
Total Completed	32	77	21	19	50	12	56	52	62	81	2	56	18	89	22	32	20	54	37	4	24	16	11	67	914
Intervention	64	162	45	41	101	17	135	93	120	133	5	105	30	162	44	109	35	120	73	16	44	34	15	125	1828

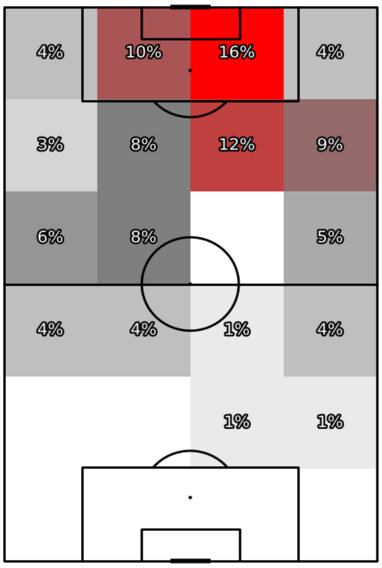
Player 14 (midfielder) made the most passes (Figure 2), with 89 interactions contributing to offensive actions, while player 2 (forward) received the highest number of passes (Figure 3), with a total of 85 interactions.

Figure 2. Passes made by player number 14 (midfielder).



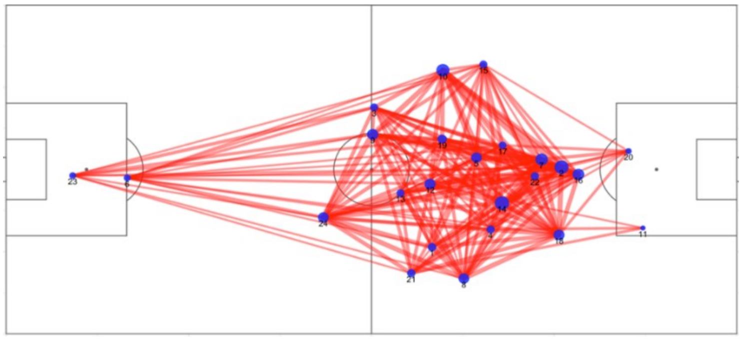
The level of interventions—defined as the sum of total passes made and received—showed that player 14 (midfielder) and player 2 (forward) had the highest intervention values, both with a total of 162 interactions.

Figure 3. Passes received by player number 2 (forward).



These players were followed by player 7 (forward), with 135 interactions, and player 10 (defender), with 133 interactions (Figure 4).

Figure 4. Network plot example of the actions that ended in finishing.



When examining the micro network metrics (Table 3), the degree centrality values (passes made) indicated that player 14 (midfielder), player 10 (defender), and player 2 (forward) contributed the most to the team's passing dynamics. For the degree prestige metric (passes received), player 2 (forward), player 7 (forward), and player 16 (forward) ranked highest, highlighting their central roles in receiving passes and facilitating offensive plays.

Table 3. Micro Network Metrics applied to network analysis in offensive actions.

Player Number	Out-Degree	In-Degree
2	0,084	0,093
10	0,089	0,057
3	0,023	0,026
22	0,018	0,020
14	0,097	0,080
5	0,055	0,056
21	0,026	0,022
7	0,061	0,086
12	0,061	0,054
13	0,020	0,013
6	0,013	0,005
16	0,022	0,016
24	0,073	0,063
15	0,024	0,024
18	0,059	0,072
4	0,021	0,024

11	0,002	0,003
8	0,057	0,045
9	0,068	0,063
20	0,004	0,013
23	0,012	0,004
16	0,035	0,084
1	0,035	0,035
19	0,040	0,039

Discussion

This study aimed to analyse the offensive actions that resulted in shots during the 2020-2021 season of the Portuguese First Division, using network analysis to evaluate differences in macro metrics (density and clustering coefficient) between the first and second halves of the season, as well as identifying key players through micro metrics (degree centrality and degree prestige).

The first hypothesis posited that there would be significant differences in the team's network metrics between the two halves of the season. However, the results indicated no statistically significant changes in density ($W = 95$, $p = 0.0912$) or clustering coefficient ($W = 112$, $p = 0.2689$), leading to reject this hypothesis. The second hypothesis predicted that certain players, particularly midfielders and forwards, would exhibit higher micro metric values, reflecting their greater contribution to offensive actions. This was confirmed by the data, with player 14 (midfielder) and player 2 (forward) emerging as the most central figures in terms of passes made and received, respectively.

Analysing both density and clustering coefficient metrics indicated that, while these macro metrics provide a comprehensive overview of team interactions, no significant differences were found between the two halves of the season. These metrics are often used to gauge overall team cohesion, with density reflecting the level of control a team exerts through possession (Immler et al., 2021; Pina et al., 2017). In this study, it was observed a slight improvement in density from the first half to the second, possibly indicating enhanced cohesion as the season progressed. Over time, teams become more familiar with each other, enhancing players' integration into team dynamics and aligning more effectively with the coach's vision for the team.

Nevertheless, the clustering coefficient decreased, suggesting that while the team became slightly more connected overall, the interconnectivity between close teammates diminished. This could reflect tactical adjustments or variations in player roles over the course of the season, which may result from changes in tactical systems or the absence of players due to injury.

The decrease in the clustering coefficient suggests a reduced level of interconnectivity between teammates, but this may not necessarily be detrimental. Previous studies indicate that clustering coefficient is not always a direct indicator of team performance (Pina et al., 2017). In this case, the team achieved its objectives for the season, suggesting that other factors may compensate for a decline in this metric, such as improvements in other areas of play, or the integration of new players after the winter transfer window. Indeed, some research shows that higher clustering coefficient values can sometimes be associated with poor team performance, particularly when over-reliance on close interactions hinders fluidity and adaptability in gameplay (Zhao & Zhang, 2020).

These findings highlight the importance of understanding tactical and contextual elements when interpreting network metrics. For example, the team's transition play (counterattacks) accounted for most offensive actions, compared to open play and set plays. Transition play typically involves quick, direct movements that may reduce the need for dense interconnectivity between players. This pattern aligns with previous studies that emphasise the importance of offensive transitions in modern football, where teams tend to perform better when exploiting these opportunities (Reep & Benjamin, 1968; McLean et al., 2017; Mclean et al., 2018; Alves et al., 2016, 2022).

As well, it is important to note that the 2020-2021 season was played during the COVID-19 pandemic, which likely influenced team dynamics. With irregular player availability and disrupted schedules, coaches and teams had to adapt quickly (Fernández-Cortés et al., 2024; Pascual Verdú et al., 2024). These external factors might have contributed to the fluctuations in team performance and network metrics, particularly as teams adjusted their tactics to cope with the circumstances.

On a micro-level, the analysis revealed that player 14 (midfielder) was the key player in terms of pass distribution (out-degree), while player 2 (forward) received the most passes (in-degree). This pattern suggests that midfielders, particularly central ones, play a crucial role in linking the team's offensive actions. The high number of interventions by player 14 highlights their centrality in dictating play and facilitating the connection between defensive and offensive phases (Alves et al., 2016; Alves et al., 2022).

Similarly, player 2 prominence in receiving passes emphasises the forward's role as a focal point in attacking actions. These findings are consistent with research that identifies forwards as key contributors in goal-scoring opportunities, especially in teams that favour direct and fast-paced styles of play (e.g., Alves et al., 2022; Aquino et al., 2020; Sarmento et al., 2020; Reigal et al., 2024). The fact that this team favoured transition play may explain the heavy reliance on the forwards to exploit space and create scoring chances.

Interestingly, the current results differ from studies that suggest central defenders or defensive midfielders typically exhibit higher degree prestige metrics, as they often act as anchors in a team's buildup (Clemente et al., 2019, 2020). The differences in the findings of this could be attributed to the team's tactical approach, where the forwards and midfielders took on more prominent roles in fast offensive transitions, rather than a possession-based buildup that involves the backline. This variation underlines the importance of considering a team's specific style when interpreting network metrics.

From a practical perspective, network analysis offers valuable insights for coaches, analysts, and researchers by providing a deeper understanding of team dynamics and individual contributions (Assunção et al., 2022; Zhao & Zhang, 2020). By identifying key players—such as player 14 (midfielder) and player 2 (forward)—coaches can develop targeted training sessions that maximise these players' strengths and enhance their roles within the overall team structure (Yu et al., 2020). For instance, drills focusing on increasing the involvement of the midfielder in distributing the ball or optimising the forward's positioning to receive key passes could improve offensive cohesion and effectiveness (Yu et al., 2020; Machado et al., 2021).

This analysis is particularly useful for opponent scouting and match preparation. Understanding the network structure not only highlights the key contributors within a team but also reveals patterns of play and areas where the team may be vulnerable. By recognising which players serve as focal points in an opponent's network and understanding their playmaking tendencies, teams can tailor defensive strategies to disrupt these key interactions, reducing the opposition's effectiveness in creating goal-scoring opportunities (Aquino et al., 2019; Martins et al., 2020; Sarmento et al., 2020; Alves et al., 2022; Gong et al., 2023).

This approach can support long-term player development and recruitment strategies. Hence, teams can use network metrics to assess player performance over time, identify emerging talent within their squads, or scout potential recruits whose playing style complements the team's tactical framework (Yu et al., 2020). By integrating network analysis into regular performance evaluations, teams can make data-driven decisions that enhance both individual and collective performance (Praça et al., 2019).

While this study offers valuable insights into offensive team dynamics through network analysis, some limitations must be acknowledged. First, the analysis focused exclusively on player networks, overlooking other critical dimensions such as pitch passing networks and spatial positioning (Herrera-Diestra et al., 2020). Incorporating spatial data could provide a more holistic understanding of team behaviour, including how players move and interact within different areas of the pitch. Such an approach would allow for a more nuanced evaluation of tactical execution and player positioning during key moments of the game.

Second, this study was confined to a single season, which may not fully reflect broader trends in team performance or account for the impact of external factors, such as tactical shifts, player fatigue, or mid-season transfers. Evaluating network metrics across multiple seasons would help capture long-term patterns and allow researchers to assess how these factors influence team dynamics over time. This approach could also identify periods of sustained improvement or decline in team performance, which are crucial for making informed strategic decisions.

Moreover, the analysis was restricted to a single team, limiting the ability to generalise findings across different playing styles, tactical systems, and levels of competition. Expanding the study to include multiple teams from various leagues and divisions would provide comparative insights, enabling a more robust understanding of how different approaches to play influence network dynamics. Additionally, studying teams with different tactical preferences (e.g., possession-based vs. counter-attacking teams) would shed light on how network structures vary based on strategic choices.

Finally, future research could explore the role of situational variables such as match status, game location (home or away), and opposition quality, which may impact network metrics. Investigating how team dynamics shift in response to these factors could offer deeper insights into a team's adaptability and resilience during different phases of the game.

Conclusions

This study indicated that network metrics provide a comprehensive understanding of team dynamics, particularly in identifying key contributors to offensive actions. Our analysis confirmed that player 2 (forward) and player 14 (midfielder) were the most central figures in the team's offensive network, playing pivotal roles in passing interactions and overall team performance. These findings highlight the importance of specific players in shaping the team's offensive strategy, particularly during transition play, which accounted for most offensive actions compared to open play and set plays.

By examining micro network metrics, such as degree prestige (in-degree) and degree centrality (out-degree), this study offers a detailed view of how individual players contribute to team performance throughout the season. These insights can be instrumental for coaches and analysts, not only in identifying key players within their own teams but also in recognising patterns in opponents' play. This level of analysis enables the development of tailored training exercises that enhance individual and collective performance, as well as more effective strategies for countering opposing teams.

This study offers practitioners tools to conduct more informed tactical assessments and design more specific training interventions. The ability to identify which players contribute the most to team performance allows for a more focused approach to player development and opponent analysis, making network analysis an asset in modern football.

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