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Article

# Exploring team dynamics through network analysis: A season review of an elite Portuguese soccer team

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**Abstract:** Social network analysis was applied to investigate team dynamics and inter-player connections during matches to offer deeper insights into the organizational framework of an elite soccer team competing in the Portuguese First Division during the 2020–2021 season. This study aimed to assess the impact of match outcomes and the deployment of various tactical systems on the team's macro network metrics, such as density and clustering coefficients. Data was collected from thirty-four matches, with each match's passing interactions meticulously analyzed to construct adjacency matrices, thereby quantifying player interconnections. The study's findings revealed a nuanced relationship between network metrics and match outcomes. Density was significantly higher in matches that ended in losses, suggesting a potential over-reliance on certain players or interactions in adverse scenarios. Conversely, matches won were characterized by higher clustering coefficients, indicating a more cohesive and interconnected team effort. The analysis of five different tactical systems revealed significant differences in density, pointing to the influence of tactical choices on player interactions. No significant differences were found in clustering coefficients across the tactical systems, suggesting a consistent internal team cohesion irrespective of the strategy employed. These insights highlight the utility of network analysis in enhancing the understanding of team dynamics and strategic planning. This study underscores the potential of such analytical approaches to inform better tactical decisions and optimize team performance, ultimately contributing to a more sophisticated level of competitive analysis in professional sports.

**Keywords:** macro perspective; soccer; performance analysis; match outcome

## 1. Introduction

Soccer remains one of the most thoroughly researched areas within sports science, particularly its strategic and tactical dimensions. The development of match plans by the technical staff is a crucial aid in helping players achieve their objectives, both collectively and individually [1,2].

The realm of soccer analysis seeks to unravel the complexities inherent in each match, involving an in-depth exploration of tactics, strategies, player performances, and statistical insights to reveal the patterns that define the beautiful game [3]. This analysis ranges from dissecting individual player movements to scrutinizing team formations, providing stakeholders with a nuanced understanding of the sport that enhances appreciation of the strategic interplay on the field [4,5].

The advent of technology has revolutionized the ways in which games are analyzed and information is prepared with the appearance and use of video analysis software, telestration software, and tracking and skeletal data. Technical staff and analysts use these technological tools to efficiently transform raw data into actionable insights both pre- and post-match [3]. Social network analysis, for instance, has proven to be an invaluable tool in examining the intricate relationships and interactions among team members, assisting coaches and analysts in identifying patterns of connectivity [6,7].

Network science has progressively become crucial in sports analysis, drawing on "Graph Theory" to understand connections between nodes [8]. In soccer, Social Network Analysis transcends traditional statistics to delve into the patterns of interaction, communication, and influence that shape team dynamics [9,10]. Researchers employ adjacency matrices to evaluate player interactions, adding metrics that characterize player behaviours and contribute to a deeper understanding of the team's dynamics [9,11].

Researchers often adopt macro and micro analytical approaches to study teams. The macro perspective focuses on a global analysis, while the micro approach delves into individual contributions within the team [12]. Our study centers on macro analysis, influenced by findings that clustering coefficients, which highlight interactions within subgroups, are fundamental in constructing passing networks that coordinate team actions effectively [13]. Another study confirmed that network density is a reliable predictor of a team's success in creating dangerous plays and scoring opportunities [14], a finding echoed by the 2022 World Cup, where top teams displayed a possession-based style [15].

While many studies focus on national teams in major tournaments like the European Championship or World Cup, others have explored club performances in the Champions League and domestic leagues [11,13,15–23]. A particular study on AS Monaco's performance in the French Ligue 1 highlighted the critical roles of defensive midfielders, box-to-box midfielders, and central defenders in the offensive process [23]. This comprehensive seasonal analysis aids coaches in refining strategic and tactical aspects, enhancing both team and opposition performance insights [23].

Moreover, contextual variables like match status, location, and opponent quality are increasingly considered in analyses [19], although few studies have explored the impact of match status and tactical systems on team macro metrics. A study of the 2018 World Cup concluded that while teams maintained consistent macrostructures regardless of match status, microstructures adapted based on playing style [19].

Despite extensive research on tactical applications in soccer, there remains a significant gap in understanding how specific tactical systems and match outcomes influence the macro network metrics of team interactions during competitive league play. Moreover, most studies have analysed both tactical systems and match outcomes in major competitions or, in most cases, with national teams [16,19].

This study aims to analyse the influence of match outcomes and tactical systems (1-4-1-4-1, 1-4-3-3, 1-3-4-3, 1-4-2-3-1, and 1-4-4-2) on the macro network metrics of a professional soccer team in the Portuguese first division during the 2020–2021 season. The selection of this sample contrasts with most studies focused on high-level teams, which typically feature more passes and involve prominent stars, providing a richer dataset for analysis. This approach allows for a broader insight into the league's dynamics and offers a fresh perspective for future research [24].

We hypothesize that higher interaction metrics will be evident in losing matches, driven by the necessity to alter match outcomes, particularly when employing 1-4-3-3 and 1-3-4-3 formations [19].

## 2. Materials and methods

### 2.1. Sample

This study analyzed thirty-four matches involving an elite soccer team from the Portuguese First Division during the 2020/2021 season. This sample size was strategically chosen to provide a comprehensive overview of the team behavior, since they had limited prior appearances in the first division [25]. Notably, during the season under review, they achieve one of the best performances in the league.

Video footage for these matches was sourced and downloaded from Wyscout, a soccer scouting and match analysis platform. The club's analyst also provided additional tactical footage.

Passing information from all matches was gathered from OPTA data, which has been used in previous studies [26,27]. The reliability of OPTA data has been verified previously (intra-class correlation coefficients: 0.88–1.00; standardized typical error: 0.00–0.37) [28].

The research adhered to the Declaration of Helsinki and received approval from the local ethics committee at the Faculty of Sports Sciences and Physical Education, University of Coimbra.

### 2.2. Study design

The study design involved the comprehensive retrieval and analysis of passing information from each match during the 2020–2021 season. An adjacency matrix was constructed for each match based on successful passes between teammates, where only uninterrupted passes were considered to ensure accuracy. The weight of each adjacency matrix was determined by the total number of passes exchanged between each pair of players in a match, culminating in the construction of 34 adjacency matrices for the season.

These matrices were then imported into the Social Network Visualizer version 3.0.4 [29], which facilitated the visualization of the network and the prior metric automatic calculation and analysis of the team and individual players. This software application was used to standardize values for each metric analyzed. Our network analysis was conducted from a macro or global perspective, focusing on team properties such as density and clustering coefficient [19]. Density was defined as the ratio between the total observed links and the maximum possible links, with values ranging from 0, indicating no density, to 1, representing maximal cooperation [19,30]. Similarly, the clustering coefficient measured the level of interconnectivity between closely connected teammates, with values also ranging from 0 to 1 [19,30]. The local clustering coefficient can be calculated by the number of links between their neighbors (vertices) divided by the number of possible links [31].

The study also considered two independent variables: match outcome and tactical system used. The match outcome included the final result of each match, categorized into losses (18), draws (6), or wins (10). The playing formation for each match was determined by the researchers and confirmed using the Wyscout platform. Throughout the season, the team employed five different tactical systems over the 34 matches: 1-4-1-4-1, 1-4-3-3, 1-3-4-3, 1-4-2-3-1, and 1-4-4-2.

### 2.3. Statistical analysis

Data was presented in various formats, including text, tables, and figures, which included means and standard deviation values. Statistical analyses were conducted using SPSS (version 26, IBM Corporation, Armonk, NY, USA), with significance levels set at 0.05. We assessed normality and homogeneity using the Shapiro-Wilk and Levene tests, respectively. Given the characteristics of our sample, we employed the Kruskal-Wallis nonparametric test to analyze the data due to our sample not meeting normality assumptions. This was followed by Dunn's post hoc tests with Bonferroni correction to evaluate differences between groups in the macro analysis. To measure the magnitude of the effects, we calculated the $r$ effect size for each pairwise comparison, classifying them as small ($r$ = 0.10), medium ($r$ = 0.30), and large ($r$ = 0.50) [32].

## 3. Results and discussion

Density metrics averaged 0.538 across all matchdays, with notable peaks on matchdays 14, 16, 30, 32, and 34. For the clustering coefficient, the average was 0.2823, with winning scenarios showing higher values ($M$ = 0.322, SD = 0.058) compared to losses ($M$ = 0.251, SD = 0.028) and draws ($M$ = 0.310, SD = 0.067). Specific matches like matchday 18 and 21 also saw higher values, suggesting specific gameplay dynamics during these games.

### 3.1. Match outcome

Levene's test indicated no significant variance among the density metric (**Table 1**) across different match outcomes ($p$ = 0.741). The Shapiro-Wilk test revealed that the density data deviated from a normal distribution ($p$ = 0.037). Results from the Kruskal-Wallis test showed no significant differences in density across the three match outcomes ($H(2)$ = 1.659, $p$ = 0.436; small effect size, $r$ = 0.0503).

Dunn's post-hoc test with Bonferroni correction indicated no significant differences between losing and drawing ($p$ = 0.731), losing and winning ($p$ = 1.00), or drawing and winning ($p$ = 1.00) regarding the density metric.

**Table 1.** Post-Hoc test and magnitude of the effect size in the match outcome and density metric.

| Variable | Group 1 | Group 2 | *N*1 | *N*2 | Statistic | *p* | p.adj | *r* | Magnitude |
|---|---|---|---|---|---|---|---|---|---|
| Density | Loosing | Drawing | 18 | 6 | −1.166 | 0.244 | 0.731 | −0.238 | Medium |
| | Loosing | Winning | 18 | 10 | −0.871 | 0.384 | 1 | −0.165 | Medium |
| | Drawing | Winning | 6 | 10 | 0.399 | 0.690 | 1 | 0.099 | Small |

For the clustering coefficient (**Table 2**), Levene's Test confirmed homogeneity of variance ($p$ = 0.8507), and the Shapiro-Wilk test indicated non-normal distribution ($p$ = 0.005). The Kruskal-Wallis test found no significant differences in clustering coefficient across match outcomes ($H(2) = 1.13$, $p = 0.568$; small effect size, $r = 0.034$). Dunn's post-hoc test showed no significant differences between losing and drawing ($p = 1.00$), losing and winning ($p = 0.885$), or drawing and winning ($p = 1.00$).

**Table 2.** Post-Hoc test and magnitude of the effect size in the match outcome and clustering coefficient metric.

| **Variable** | **Group 1** | **Group 2** | ***N*1** | ***N*2** | **Statistic** | ***p*** | **p.adj** | ***r*** | **Magnitude** |
|---|---|---|---|---|---|---|---|---|---|
| Density | Loosing | Drawing | 18 | 6 | 0.486 | 0.627 | 1 | 0.099 | Small |
| | Loosing | Winning | 18 | 10 | 1.05 | 0.295 | 0.885 | 0.198 | Medium |
| | Drawing | Winning | 6 | 10 | 0.357 | 0.721 | 1 | 0.089 | Small |

### 3.2. Tactical system

Levene's test indicated no significant variance among the density metric (**Table 3**) across different tactical systems ($p = 0.373$). The Kruskal-Wallis test identified significant differences in the density metric (**Table 3**) across the five tactical systems ($H(4) = 11.249$, $p = 0.024$; large effect size, $r = 0.341$). Dunn's post-hoc test with Bonferroni correction highlighted significant differences between the 1-4-2-3-1 and 1-4-4-2 systems ($p = 0.028$; large effect size).

**Table 3.** Post-Hoc test and magnitude of the effect size in the tactical system and density metric.

| **Variable** | **Group 1** | **Group 2** | ***N*1** | ***N*2** | **Statistic** | ***p*** | **p.adj** | ***r*** | **Magnitude** |
|---|---|---|---|---|---|---|---|---|---|
| Density | 1-4-1-4-1 | 1-4-3-3 | 8 | 9 | 1.153 | 0.249 | 1.000 | 0.280 | Medium |
| | 1-4-1-4-1 | 1-3-4-3 | 8 | 11 | −0.038 | 0.970 | 1.000 | −0.009 | Small |
| | 1-4-1-4-1 | 1-4-2-3-1 | 8 | 4 | 2.122 | 0.034 | 0.339 | 0.612 | Large |
| | 1-4-1-4-1 | 1-4-4-2 | 8 | 2 | −1.628 | 0.104 | 1.000 | −0.515 | Large |
| | 1-4-3-3 | 1-3-4-3 | 9 | 11 | −1.285 | 0.199 | 1.000 | −0.287 | Medium |
| | 1-4-3-3 | 1-4-2-3-1 | 9 | 4 | 1.230 | 0.219 | 1.000 | 0.341 | Large |
| | 1-4-3-3 | 1-4-4-2 | 9 | 2 | −2.362 | 0.018 | 0.182 | −0.712 | Large |
| | 1-3-4-3 | 1-4-2-3-1 | 11 | 4 | 2.256 | 0.024 | 0.241 | 0.582 | Large |
| | 1-3-4-3 | 1-4-4-2 | 11 | 2 | −1.651 | 0.099 | 0.988 | −0.458 | Large |
| | 1-4-2-3-1 | 1-4-4-2 | 4 | 2 | −2.986 | 0.003 | 0.028 | −1.219 | Large |

For the clustering coefficient, Levene's test indicated no significant variance among the clustering coefficient metric (**Table 4**) across different tactical systems ($p = 0.546$).

The Kruskal-Wallis test found no significant differences across the five tactical systems ($H(4) = 4.318$, $p = 0.365$; medium effect size, $r = 0.131$). Dunn's post-hoc test revealed no significant differences across the tactical systems.

**Table 4.** Post-Hoc test and magnitude of the effect size in the tactical system and clustering coefficient metric.

| Variable | Group 1 | Group 2 | *N*1 | *N*2 | Statistic | *p* | p.adj | *r* | Magnitude |
|---|---|---|---|---|---|---|---|---|---|
| Clustering coefficient | 1-4-1-4-1 | 1-4-3-3 | 8 | 9 | −1.241 | 0.215 | 1.000 | −0.301 | Medium |
| | 1-4-1-4-1 | 1-3-4-3 | 8 | 11 | −1.947 | 0.052 | 0.516 | −0.447 | Large |
| | 1-4-1-4-1 | 1-4-2-3-1 | 8 | 4 | −1.313 | 0.189 | 1.000 | −0.379 | Large |
| | 1-4-1-4-1 | 1-4-4-2 | 8 | 2 | −1.208 | 0.227 | 1.000 | −0.382 | Large |
| | 1-4-3-3 | 1-3-4-3 | 9 | 11 | −0.671 | 0.502 | 1.000 | −0.150 | Medium |
| | 1-4-3-3 | 1-4-2-3-1 | 9 | 4 | −0.334 | 0.738 | 1.000 | −0.093 | Small |
| | 1-4-3-3 | 1-4-4-2 | 9 | 2 | −0.450 | 0.653 | 1.000 | −0.136 | Medium |
| | 1-3-4-3 | 1-4-2-3-1 | 11 | 4 | 0.172 | 0.863 | 1.000 | 0.044 | Small |
| | 1-3-4-3 | 1-4-4-2 | 11 | 2 | −0.065 | 0.948 | 1.000 | −0.018 | Small |
| | 1-4-2-3-1 | 1-4-4-2 | 4 | 2 | −0.174 | 0.862 | 1.000 | −0.071 | Small |

## 4. Discussion

The primary aim of this study was to analyse the influence of match outcomes and tactical systems on the macro network metrics of a professional soccer team competing in the Portuguese First Division during the 2020–2021 season. Our findings revealed no significant differences in density or clustering coefficient across match outcomes. However, significant differences in density were observed among the five tactical systems employed, whereas no significant differences were found in clustering coefficients across these systems. These results align partially with previous studies, which suggest that macro network metrics alone may not consistently serve as predictors of success [19].

Network density, a key indicator of overall team cooperation, has been identified as a potential predictor of offensive success [14]. The average density in our study (0.538) reflects moderate team cohesion and aligns with the team's overall performance, as they achieved their seasonal objectives with a comfortable league position [25]. Density tends to increase in scenarios where teams control the ball more effectively, reflecting higher pass frequency and fewer turnovers possession [13,14]. Notably, our findings support the assertion that higher density values are often associated in losing situations, as teams attempt to dominate possession in search of goals [19]. Although we analysed only one team from the Portuguese league, this finding may still reflect the league's overall characteristics. Future studies could further investigate this to identify the defining traits of different soccer leagues.

Comparisons with elite teams, such as those coached by Pep Guardiola, reinforce the link between high density and possession-based soccer. Guardiola's teams exhibit high density values, highlighting their controlled, pass-heavy approach [13]. Conversely, trends from the 2010 and 2018 FIFA World Cups indicate a shift toward more direct play with reduced density and fewer passing interactions. Interestingly, high-performing teams in the 2022 World Cup returned to a possession-based style, suggesting that density remains a critical metric for understanding evolving tactical trends [15]. Moreover, it is important to highlight that teams can develop greater cohesion and cooperation as they evolve over time [25].

In contrast, clustering coefficient values, which measure interconnectivity among closely linked teammates, were higher in won matches in our study. These findings are consistent with studies from international tournaments like the 2018 FIFA World Cup, where winners displayed greater interconnectivity [16,18]. This trend suggests that winning teams may rely on tightly coordinated subgroups to execute tactical plans effectively. Greater interconnectivity could reflect a team's ability to maintain strong localized connections, fostering cohesive and efficient movement across the field. However, it's important to note that clustering coefficient is not always a direct indicator of team performance [14] and can, at times, be associated with poor performance [33].

Our analysis of tactical systems revealed interesting patterns. The 1-4-3-3 and 1-4-2-3-1 systems exhibited higher density values, indicating greater ball control and cohesion in these setups. Similarly, higher clustering coefficients were observed in the 1-4-3-3 and 1-4-1-4-1 formations, reflecting stronger interconnectivity. Significant differences in density were identified between the 1-4-2-3-1 and 1-4-4-2 systems, underscoring the impact of formation on team dynamics. However, consistent with previous research [16] clustering coefficients did not show significant differences across tactical systems, suggesting that interconnectivity may be less influenced by formation and more by broader team strategy and cohesion.

Macro network metrics provide valuable insights into team organization and offensive dynamics. Studies suggest these metrics are essential for understanding collective team behavior and offer coaches a global perspective on performance [12,16]. Visualization of passing networks and network metrics also allows for the identification of individual contributions, tactical adjustments, and evolving team dynamics throughout matches or across a season [24]. These insights can be particularly useful in identifying specific patterns that distinguish successful teams from less successful ones, offering a quantitative foundation for performance improvement.

Our findings have practical implications for coaches, offering a framework to refine game models and adapt playing styles based on available players and tactical objectives. Network analysis highlights the importance of tailoring strategies to optimize interactions and team cohesion [11,16]. Moreover, the absence of significant differences in network metrics across formations suggests that modern players are increasingly versatile, capable of performing effectively in various tactical setups. This underscores the importance of comprehensive training programs and strategic preparation to ensure flexibility and adaptability in competitive scenarios [23].

The context of this study, conducted during the COVID-19 pandemic, adds a unique dimension to the analysis. The pandemic significantly impacted player fitness, match schedules, and preparation, potentially influencing the results [34,35]. Coaches and analysts must consider these and other factors, such as injuries or suspensions, when interpreting the findings and applying them in practice [25].

Despite its strengths, this study has its limitations. First, it focuses on a single team in the Portuguese First Division, limiting the generalisability of the findings. While previous studies often analyse elite teams like FC Barcelona [17], this is one of the few to examine a mid-tier team in this league [25]. Future research should broaden its scope to include multiple teams across different leagues to enhance the applicability of findings.

Second, this study primarily analyzed macro metrics, providing a high-level view of team dynamics. Complementary analysis of micro metrics, which focus on individual contributions, would offer deeper insights into player-specific roles and interactions [16]. Dynamic network analysis, incorporating time windows or pitch-based passing networks, could further enhance our understanding of temporal and spatial dynamics within matches [7,36,37]. Additionally, incorporating defensive metrics would provide a more holistic view of team performance [23,38]. If available, the use of spatiotemporal data could enhance and facilitate the identification of the tactical systems used by the team [39].

Finally, this study highlights the value of macro network metrics as a tool for understanding team dynamics and informing tactical decisions. Coaches can leverage these insights to develop tailored strategies that enhance team performance, considering the evolving nature of modern soccer. Future studies should explore the integration of macro and micro metrics, dynamic analyses, and multi-season data to further refine our understanding of soccer's intricate dynamics. Furthermore, expanding research to examine defensive structures and their interaction with offensive metrics could provide a more comprehensive framework for analyzing team performance.

## 5. Conclusion

Network analysis has proven to be a valuable tool for understanding team dynamics, offering both a clearer characterization of a team's organization and a more detailed framework for analyzing opponents. This study demonstrates that macro network metrics provide insights into how teams adapt to different match scenarios and how their tactical systems influence overall cohesion and interconnectivity.

The analysis of a complete season revealed that teams often adjust their dynamics in losing situations, likely driven by the necessity to dominate possession and create opportunities to reverse the outcome. Additionally, examining the tactical systems used highlighted how specific formations can impact team organization and player interactions. Such insights allow coaches to identify which systems enable their teams to perform optimally, providing a foundation for strategic adjustments during both training and competition.

The findings of this study have clear practical applications for coaches and analysts. First, network analysis can guide coaches in evaluating the strengths and weaknesses of their current tactical systems, allowing them to refine their game models to enhance team performance. Second, it can aid in designing tailored training exercises that replicate the specific interactions and scenarios observed in matches, thereby improving team cohesion and adaptability. Third, coaches can use network metrics to better understand the capabilities of individual players within various tactical setups, ensuring that roles and responsibilities are optimally assigned.

Future applications of network analysis should extend to integrating defensive metrics, dynamic network models, and cross-league comparisons to provide an even more comprehensive understanding of team behavior. By leveraging these insights, teams can achieve not only greater tactical awareness but also long-term competitive advantages in a rapidly evolving soccer landscape.

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