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Positional Influence in Football Passing Networks: An Analysis of the Tactical Systems and Match Outcomes

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Abstract

This study analysed how tactical systems and match outcomes influence micro-level passing network metrics across playing positions in a professional football team competing in the Portuguese First Division during the 2020–2021 season. It examined how structural variation affects Degree Centrality, Degree Prestige, and Proximity Prestige across tactical systems (1-4-1-4-1, 1-4-3-3, 1-3-4-3) and outcomes (win, loss, draw) in different positions. Data from 28 league matches were used, with adjacency matrices constructed from teammate interactions. Players were grouped into six positions: goalkeepers, fullbacks, central defenders, central midfielders, wingers, and strikers. One-way ANOVA revealed significant differences ($p < 0.05$) across positions, tactical systems, and match outcomes. Central defenders consistently showed higher values of Degree Centrality and Degree Prestige across most systems and outcomes, highlighting their structural importance. In contrast, strikers and wingers displayed greater Proximity Prestige in the 1-4-3-3 and 1-3-4-3, reflecting their offensive positioning. Match outcome analysis indicated that wingers had significantly higher Degree Prestige in won matches compared to losses. Overall, results show that micro-level network metrics vary meaningfully by position and context, underscoring the importance of interpreting them cautiously. Despite the novelty of this study, focusing on the initial tactical systems without capturing within-match adjustments may condition the generality of the results. Coaches and practitioners should account for tactical and outcome-related variations when applying network analysis to optimise team dynamics.

Keywords: match analysis; soccer; network analysis; performance analysis; new technologies

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1. Introduction

New technologies in football have become a prominent arena of study within the research community, with the number of studies increasing steadily [1,2], as teams seek to improve performance in comparison with their opponents. But more than a performance improvement, this also enabled a more practical comprehension of the game itself, supporting coaches and practitioners designing training tasks, analysing performance, match strategy, and individual player development [3,4].

Among these approaches, Social Network Analysis offers a powerful framework to examine how teams and players act in context [5]. Particularly in football, one way to measure connections between players is through passes. This concept derives from the "Graph Theory" and indicates the connections between nodes (players), and the connection within these nodes [6]. This type of analysis goes beyond the traditional statistical methods [7,8], as it evaluates the interactions, patterns within a team, role of players, and how these communicate. To explore these connections, researchers use an adjacency matrix, which allows for the analysis of specific network metrics to gain deeper insights into team and player behaviours [7,9]. By visualising and quantifying the relationships between players, Social Network Analysis sheds light on information flow, leadership dynamics, and collective cohesion, offering coaches valuable insights into how players contribute to team organisations [10].

When studying teams and players through network analysis, it is common to adopt two levels of analysis: macro and micro. Macro analysis focuses on the overall team structure and connectivity, providing a global perspective of team dynamics. In contrast, micro analysis focus on individual player contributions, aiming to understand how each player influences and supports the team's tactical behaviour and interactions [11]. For instance, a previous study in the French First Division (Ligue 1), found that the defensive midfielder, box-to-box midfielder, and central defender were the most influential players based on network metrics [12]. Also, experienced players tend to have a greater collective impact on the team's offensive process [11].

Network analysis has been focusing on three metrics: the Degree Centrality, Degree Prestige, and Proximity Prestige. Degree prestige can be considered an indicator of a player's capacity to receive the ball from his teammates [13], and in some studies the midfielders can be a link to the teammates to receive the ball [14]; Degree Centrality provides general information of how a player connects between his teammates, and defensive midfielders and central defenders can be considered influent players regarding this [14]; Lastly, Proximity Prestige can be described as the capacity of a player to be accessible by his teammates [12]. A study at the 2014 FIFA World Cup showed that central midfielders presented the highest values in Degree Centrality, Degree Prestige, closeness centrality, and betweenness centrality across most teams [15]. Analysis of Switzerland's national team at the same tournament also highlighted midfielders' prominence in organising team dynamics [16]. Other studies showed that wingers and attacking midfielders often drive offensive actions, while fullbacks frequently initiate attacking organisation [17].

Analysing levels and metrics alone can become reductionist and not show the reasons why teams and players adopt certain behaviours. Therefore, using situational variables like tactical systems and match outcome can help to understand the context and complement team and player analysis. For example, winning teams often adopt a more direct style of play, while losing teams favour possession-based approaches, influencing player prominence [18]. Strikers may also show higher Degree Prestige due to their proximity to goal in losing situations [19]. Furthermore, successful outcomes have also been associated with increased involvement of midfielders, wingers, and forwards within the network, reflecting their involvement in maintaining possession and creating scoring chances [18].

Nevertheless, combining Social Network Analysis with tactical systems offers valuable insights [20]. As teams often adopt various strategies to counter specific opponents, identifying the most effective tactical system based on playing position becomes crucial. Network analysis facilitates a better understanding of player interactions, thereby supporting more informed and effective tactical decisions [20]. That said, previous studies suggested higher values of Degree Centrality and Degree Prestige were observed when teams employed the 1-4-2-3-1 and 1-4-3-3 tactical systems, compared with 1-4-4-2 [20]. Additionally, forwards may engage more in passing in 1-4-2-2-2 tactical system than in 1-4-2-3-1, while defensive midfielders demonstrated higher values of betweenness centrality in the 1-4-2-3-1 [21].

Despite previous research, it is important to note that most existing studies have predominantly focused on national teams [18–20] and top-level European teams [12,22–26], with relatively fewer examining mid-table teams performances in domestic competitions. This highlights a notable gap in the literature, particularly concerning the analysis across an entire season [27]. Moreover, limited attention has been given to how specific tactical systems influence the performance of individual playing positions, mainly through the lens of network metrics. Therefore, the aim of this study was twofold: (1) analyse the influence of tactical systems on playing positions, using micro-level network metrics; and (2) analyse how match outcomes affect playing positions, using micro-level network metrics in a professional Portuguese First Division team during the 2020–2021 season.

It is expected that (i) central defenders and midfielders would exhibit higher values in the network metrics than other playing positions in 1-4-3-3 and 1-4-1-4-1 tactical systems [12,14,20], and (ii) central midfielders and strikers would show greater involvement in lost matches [19]. To our knowledge, this is one of the few studies to examine the influence of tactical systems and match outcomes on playing positions usings Social Network Analysis. Addressing this gap can then provide valuable insights for both coaches and researchers by deepening their understanding of how player performance adjusts in response to the tactical structures deployed over the course of a season, focused on a mid-table team.

2. Materials and Methods

2.1. Sample

Twenty-eight matches of a male professional football team competing in the Portuguese First Division during the 2020/2021 season were included for analysis in this study. The sample size was chosen since the team had limited appearances in the First Division, and during this season they achieved one of their best performances [27]. Choosing a team whose objective is to maintain its position in the First Division contrasts with most existing studies, which tend to focus on national teams [18,20] or top-tier clubs competing in the UEFA Champions League [28].

Match video footage was accessed and downloaded from football scouting and match analysis platform, Wyscout (Italy) [29,30], and the tactical footage of the match granted from the club's performance analyst.

Events from the matches were gathered from OPTA data (United Kingdom), which has been used in previous studies [31,32]. It was only focused on retrieving passing information from the matches. The reliability of OPTA data has been verified previously (intra-class correlation coefficients: 0.88–1.00; standardised typical error: 0.00–0.37) [33].

The study was conducted in accordance with the Declaration of Helsinki and was approved by the ethics committee at the Faculty of Sports Sciences and Physical Education, University of Coimbra.

2.2. Study Design

All passing information from each of the twenty-eight matches was retrieved for analysis. For each match an adjacency matrix was constructed based on the teammate's interactions. 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 28 adjacency matrices for our analysis [27].

For every match, an adjacency matrix was imported into the Social Network Visualizer version 3.0.4 [34], which allows the visualisation of the network and prior metric analysis of the team and players (nodes). For this study, the standardised values were used for each metric [12].

For the network analysis, it was analysed only from a micro or player perspective. Following the approach of related studies [27] and maintaining a sequential rationale, the following was adopted:

(i) Degree Centrality (the standardised Degree Centrality or out-Degree Centrality that indicates the overall level of connection performed of a player with their teammates (passes completed)). The algorithm, observed in previous works [35], stands as $\mathrm{DC}^{\mathrm{w}}_{\text{D-out}}(\mathrm{n_i}) = \mathrm{k_i^{w-out}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{a_{ij}}$, in which a_{ij} can be considered the elements of the weighted adjacency matrix of a G with a n_i as a vertex.

(ii) Degree Prestige (the standardised Degree Prestige or in-Degree Centrality, which indicates the number of inbound links received by a player by their teammates (passes received)). The algorithm can be observed as $DP^{w}_{D\text{-}in} = k_i^{w} = \sum_{j=1}^{n} a_{ji}$, in which a_{ij} can be considered the elements of the weighted adjacency matrix of a G with a n_i as vertex [35].

(iii) Proximity Prestige (the capacity of a player to be accessible to teammates). Here, the algorithm is: $d^{w}(n_i, n_j)$ [35], in which is the shortest path between vertices ni and nj [10,12,27,35].

Like the network macro metrics, the values range from 0—none or lack of density—to 1—maximal cooperation [10,18]. The study considered three independent variables: playing position, tactical system, and match outcome.

The playing positions were classified and adapted for the statistical analysis [36]: goalkeeper (GK, n = 3 players), fullback (FB, n = 4 players), central defender (CD, n = 5 players), central midfielder (CM, n = 6 players), winger (WG, n = 4 players), and striker (ST, n = 4 players). For each match, individual metrics were recorded for all players who played. Subsequently, position-specific averages were calculated. For example, when two central defenders participated in a match, their individual metrics were first analysed and then averaged to represent the performance of the central defenders' position for that match. The same procedure was applied when additional players, such as a third central defender introduced through substitution, contributed during the match. Playing time was not considered in this study, and all players were included regardless of their minutes played, as the focus was on positional contributions within the tactical structures rather than on individual workload.

Regarding tactical systems, a total of three were recorded during the season: (i) 1-4-1-4-1 (n = 8); (ii) 1-4-3-3 (n = 9); and (iii) 1-3-4-3 (n = 11) (Figure 1). Regarding the absence of specific data (e.g., tracking data) to clearer identify the tactical system, playing formation was determined by the researchers and confirmed by the Wyscout platform. Only the initial tactical system used at the start of each match was considered, and any changes or variations occurring during the game were not included in the analysis [21]. However, while in-match adjustments are undoubtedly important, focusing on the initial tactical system allows for the examination of the coach's strategic intent and planned positional responsibilities, which form the foundation for subsequent adaptations. The players' positions across different tactical systems were not considered; for example, fullbacks were grouped together regardless of whether they played in a 1-4-3-3 or a 1-3-4-3 formation.

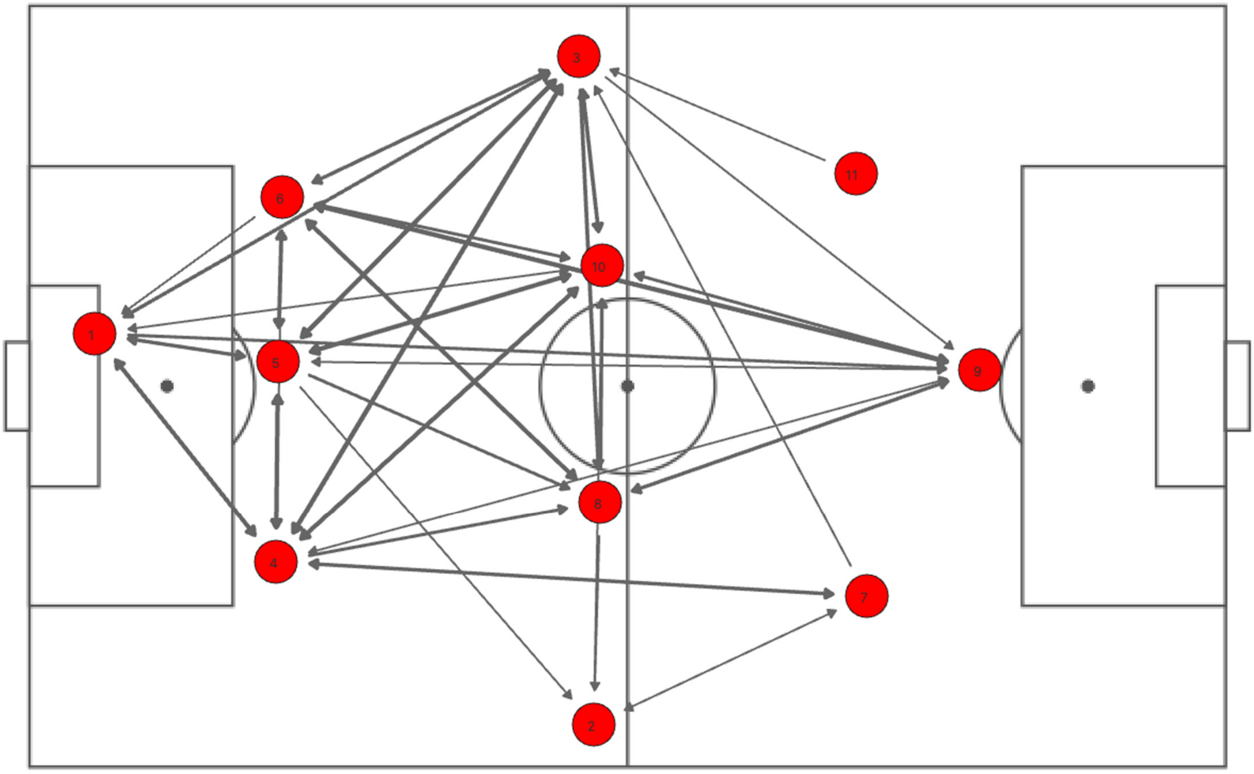

Figure 1. Example of players positioning on the pitch on the 1-3-4-3 tactical system.

Finally, for the match outcomes, only the three possible results in football were considered: win (n = 9), lose (n = 14) and draw (n = 5).

2.3. Data Analysis

Statistical analysis of interactions between playing position and tactical system as well as playing position and match result in the network metrics degree centrality, proximity prestige, and degree prestige was conducted with a two-way ANOVA after checking the normality and homogeneity assumptions [37].

The normality assumption of the different variables within the different groups, defined by the crossing of the independent variables, was assessed using the Shapiro–Wilk test ($n < 30$) [38,39], as it provides a robust evaluation of normality in small and moderate samples. In cases where the assumption of normality was not verified, symmetry analysis was used using the following condition [40]:

$$|\,Skewness/Std\ error\ Skewness\,| \leq 1.96$$

To verify the assumption of homogeneity, the Levene statistical test was used. When the interaction between the ANOVA two-way factors was statistically significant, a new variable was created that resulted from the crossing of the factors for each dependent variable. After this, a one-way ANOVA was conducted for the newly created factor (based on the interaction), after checking the normality and homogeneity assumptions [37] followed by Tukey HSD post hoc test.

In cases where no statistically significant interaction was found, separate one-way ANOVAs were conducted to examine the main effects of each independent variable. In these cases, tactical system was fixed to analyse the effect of playing position; playing position was fixed to analyse the effect of tactical system; match result was fixed to analyse the effect of playing position; and playing position was also fixed to analyse the effect of match result on the network metrics. In all cases, assumptions of normality and homogeneity were verified prior to analysis, and Tukey HSD post hoc tests were applied when appropriate [37]. For multiple comparisons, Tukey HSD post hoc tests were applied when the assumption of homogeneity was verified [39], while Games–Howell test was used if the homogeneity assumption was not verified [39].

Effect sizes for two-way ANOVA and one-way ANOVA were estimated using η_p^2 and η^2, respectively, and classified according to established guidelines [39,41]: a very high effect was defined as values greater than 0.50, a high effect as values between 0.25 and 0.50, a moderate effect as values between 0.05 and 0.25, and a small effect as values less than or equal to 0.05 [38,40].

All statistical analysis was conducted using IBM SPSS Statistics software (version 29, IBM USA) for a significance level of 5% ($p < 0.05$).

3. Results

3.1. Playing Position x Tactical System

The results did not indicate that the interaction between the playing position and the tactical system was statistically significant in each of the network metrics: degree centrality ($F(10, 150) = 1.564$; $p = 0.123$; $\eta^2 = 0.094$, medium effect size), proximity prestige ($F(10, 150) = 0.640$; $p = 0.777$; $\eta^2 = 0.041$, small effect size), and degree prestige ($F(10, 150) =1.488$; $p = 0.149$; $\eta^2 = 0.090$, medium effect size). Consequently, an individual study of each independent variable was conducted using the ANOVA one-way.

3.1.1. Effects of Tactical Systems on Network Metrics Across Playing Position

The results (Table 1) revealed only one statistically significant difference in the central defenders across tactical systems in the Proximity Prestige metric ($F(2, 25) = 3.420$; $p = 0.049$; $\eta^2 = 0.21$, moderate effect). Tukey post hoc tests identified that proximity prestige was significantly higher in the 1-4-1-4-1 compared to 1-4-3-3 tactical system (mean difference = 0.067, $p = 0.05$).

Table 1. One-way ANOVA results for the effects of tactical systems on network metrics across playing position.

Playing Position	Degree Centrality				Proximity Prestige				Degree Prestige			
	F	p	η^2	Effect Size	F	p	η^2	Effect Size	F	p	η^2	Effect Size
goalkeepers	1.802	0.186	0.12	Moderate Effect	0.215	0.808	0.01	Small Effect	2.862	0.076	0.19	Moderate Effect
central defenders	1.162	0.329	0.08	Moderate Effect	3.420	**0.049**	0.21	Moderate Effect	1.144	0.335	0.08	Moderate Effect
fullbacks	1.365	0.274	0.09	Moderate Effect	0.116	0.891	0.01	Small Effect	0.553	0.582	0.04	Small Effect
central midfielders	1.881	0.173	0.13	Moderate Effect	1.095	0.350	0.08	Moderate Effect	2.149	0.138	0.14	Moderate Effect
wingers	1.402	0.265	0.10	Moderate Effect	2.174	0.135	0.14	Moderate Effect	1.641	0.214	0.11	Moderate Effect
strikers	1.741	0.198	0.12	Moderate Effect	0.170	0.844	0.01	Small Effect	1.726	0.198	0.12	Moderate Effect

3.1.2. Effects of Playing Position on Network Metrics Across Tactical Systems

Statistically significant differences were found between most of the tactical systems within each playing position for any of the network metrics (Table 2).

In the 1-4-1-4-1 tactical system, for degree centrality, the one-way ANOVA revealed a significant effect in the playing positions ($F(5, 42) = 17.612$; $p = 0.001$; $\eta^2 = 0.68$, very high effect). Games-Howell post hoc tests demonstrated that central defenders had higher degree centrality values than central midfielders (mean difference = 0.042, $p = 0.014$), wingers (mean difference = 0.069, $p < 0.001$) and strikers (mean difference = 0.094, $p < 0.001$). Degree prestige showed a significant effect in playing positions (F(5, 42) = 5.972; $p = 0.001$; $\eta^2 = 0.42$, High Effect); central defenders presented higher values than wingers (mean difference = 0.045, $p = 0.014$) and strikers (mean difference = 0.062, $p = 0.003$).

Table 2. One-way ANOVA results for the effects of playing position on network metrics across tactical systems.

Tactical System	Degree Centrality				Proximity Prestige				Degree Prestige			
	F	p	η2	Effect Size	F	p	η2	Effect Size	F	p	η2	Effect Size
1-4-1-4-1	17.612	**0.001**	**0.68**	Very High Effect	0.993	0.434	0.11	Moderate Effect	5.972	**0.001**	0.42	High Effect
1-4-3-3	19.726	**0.001**	**0.67**	Very High Effect	3.398	**0.010**	0.26	High Effect	6.235	**0.001**	0.39	High Effect
1-3-4-3	18.568	**0.001**	**0.61**	Very High Effect	4.107	**0.003**	0.26	High Effect	8.712	**0.001**	0.42	High Effect

In the 1-4-3-3 tactical system, for degree centrality, the one-way ANOVA revealed a significant effect in the playing positions (F(5, 48) = 19.726; $p = 0.001$; $\eta^2 = 0.67$ Very High Effect). Games-Howell post hoc test demonstrated that fullbacks, central defenders and central midfielders presented higher values than wingers and strikers (all $p < 0.01$). In the Proximity Prestige the one-way ANOVA revealed a significant effect in the playing positions (F(5, 48) = 3.398; $p = 0.010$; $\eta^2 = 0.26$ High Effect). Games-Howell post hoc test demonstrated that strikers presented higher values than fullbacks (mean difference = 0.086, $p = 0.004$), central defenders (mean difference = 0.117, $p = 0.010$) and wingers (mean difference = 0.056, $p = 0.041$). In the Degree Prestige the one-way ANOVA revealed a significant effect in the playing positions (F(5, 48) = 6.235; $p = 0.001$; $\eta^2 = 0.39$ High Effect). Games-Howell post hoc test demonstrated that fullbacks, central defenders and central midfielders presented higher values than goalkeepers (all $p < 0.05$).

In the 1-3-4-3 tactical system, for Degree Centrality, the one-way ANOVA revealed a significant effect in the playing positions (F(5, 60) = 18.568; $p = 0.001$; $\eta^2 = 0.61$ very high effect). Games–Howell post hoc test demonstrated that central defenders presented higher values than central midfielders (mean difference = 0.031, $p = 0.003$), wingers (mean difference = 0.022, $p = 0.071$) and strikers (mean difference = 0.045, $p < 0.001$). In the proximity prestige the one-way ANOVA revealed a significant effect in the playing positions (F(5, 60) = 4.107; $p = 0.003$; $\eta^2 = 0.26$ high effect). Tukey HSD post hoc tests demonstrated that wingers and strikers presented higher values than goalkeepers (mean difference = 0.074, $p = 0.024$ and mean difference = 0.071, $p = 0.032$). In the Degree Prestige the one-way ANOVA revealed a significant effect in the playing positions (F(5, 60) = 8.712; $p < 0.001$; $\eta^2 = 0.42$ High Effect). Tukey HSD post hoc tests, demonstrated that central defenders presented higher values than goalkeepers (mean difference = 0.043, $p < 0.001$) and strikers (mean difference = 0.041, $p < 0.001$). Lastly, central midfielders presented higher values than goalkeepers (mean difference = 0.022, $p = 0.043$) and strikers (mean difference = 0.023, $p = 0.035$).

3.2. Playing Position x Match Outcome

The results did not indicate that the interaction between the playing position and the match outcome was statistically significant in each of the network metrics: Degree Centrality (F(10, 150) = 1.315; $p = 0.227$; $\eta^2 = 0.081$, medium effect size), Proximity Prestige (F(10, 150) = 0.747; $p = 0.679$; $\eta^2 = 0.047$, small effect size), and Degree Prestige (F(10, 150) = 0.922; $p = 0.515$; $\eta^2 = 0.058$, medium effect size). Consequently, an individual study of each independent variable was made using the ANOVA one-way.

3.2.1. Effects of Match Outcome on Network Metrics Across Playing Position

The results (Table 3) revealed statistically significant difference in wingers across match outcomes in Degree Prestige (F(2, 25) = 5.874; p = 0.008; η^2 = 0.320, moderate effect). Tukey HSD post hoc tests showed that wingers exhibited significantly higher Degree Prestige in won matches compared to lost outcomes (mean difference = 0.016, p = 0.018).

Table 3. One-way ANOVA results for the effects of match outcome on network metrics across playing position.

Playing Position	Degree Centrality				Proximity Prestige				Degree Prestige			
	F	***p***	**η^2**	**Effect Size**	**F**	***p***	**η^2**	**Effect Size**	**F**	***p***	**η^2**	**Effect Size**
goalkeepers	0.670	0.521	0.051	Moderate Effect	0.401	0.674	0.031	Small Effect	0.002	0.998	0.000	Small Effect
central defenders	0.988	0.386	0.073	Moderate Effect	1.987	0.158	0.137	Moderate Effect	0.997	0.383	0.074	Moderate Effect
fullbacks	1.033	0.371	0.076	Moderate Effect	1.962	0.162	0.136	Moderate Effect	0.462	0.635	0.073	Moderate Effect
central midfielders	3.088	0.063	0.198	Moderate Effect	0.527	0.597	0.040	Small Effect	2.510	0.102	0.167	Moderate Effect
wingers	2.684	0.088	0.177	Moderate Effect	0.144	0.867	0.011	Small Effect	5.874	**0.008**	0.320	Moderate Effect
strikers	1.018	0.376	0.075	Moderate Effect	0.191	0.827	0.015	Small Effect	0.675	0.518	0.051	Moderate Effect

3.2.2. Effects of Playing Position on Network Metrics Across Match Outcomes

Playing position also demonstrated a significant effect on network metrics within each match outcome (Table 4).

Table 4. One-way ANOVA results for the effects of playing position on network metrics across match outcomes.

Match Status	Degree Centrality				Proximity Prestige				Degree Prestige			
	F	***p***	**η^2**	**Effect Size**	**F**	***p***	**η^2**	**Effect Size**	**F**	***p***	**η^2**	**Effect Size**
Drawn	5.649	**0.001**	**0.54**	Very High Effect	0.491	0.779	0.09	Small Effect	1.501	0.227	0.24	Moderate Effect
Lost	26.895	**0.001**	**0.63**	Very High Effect	2.468	**0.040**	0.14	Moderate Effect	8.373	**0.001**	**0.35**	**High Effect**
Won	21.714	**0.001**	**0.69**	Very High Effect	3.477	**0.009**	0.27	High Effect	10.126	**0.001**	**0.51**	Very High Effect

In drawn matches, for Degree Centrality, the one-way ANOVA revealed a significant effect in playing position (F(5, 24) = 5.649, p = 0.001, η^2 = 0.54, Very High Effect). Tukey HSD post hoc tests demonstrated that fullbacks and central defenders had higher Degree Centrality than wingers and strikers (all p < 0.05).

In lost matches, for Degree Centrality, the one-way ANOVA revealed a significant effect in playing position (F(5, 78) = 26.895, p < 0.001, η^2 = 0.63, Very High Effect). Post hoc tests (Tukey HSD) indicated that central defenders had significantly higher Degree Centrality than goalkeepers (mean difference = 0.026, p = 0.006), fullbacks (mean difference = 0.024, p = 0.019), central midfielders (mean difference = 0.030, p = 0.001), wingers (mean difference = 0.056, p < 0.001) and strikers (mean difference = 0.075, p < 0.001). For Proximity Prestige, the one-way ANOVA was significant (F(5, 78) = 2.47, p = 0.040, η^2 = 0.14, moderate effect). However, post hoc tests (Tukey HSD) did not reveal any significant pairwise differences (all p > 0.05). For Degree Prestige, the one-way ANOVA was significant (F(5, 78) = 8.37, p < 0.001, η^2 = 0.35, High Effect). Games–Howell post hoc tests showed that central defenders had significantly higher Degree Prestige than goalkeepers (mean difference = 0.044, $p < 0.001$), wingers (mean difference = 0.035, $p < 0.004$), and strikers (mean difference = 0.040, $p < 0.017$).

In won matches, for Degree Centrality, the one-way ANOVA revealed a significant effect of playing position ($F(5, 48) = 21.71$, $p < 0.001$, $\eta^2 = 0.69$, Very High Effect). Games–Howell post hoc tests showed central defenders had significantly higher Degree Centrality than goalkeepers (mean difference = 0.049, $p = 0.012$), central midfielders (mean difference = 0.051, $p = 0.002$), wingers (mean difference = 0.057, $p < 0.001$), and strikers (mean difference = 0.089, $p < 0.001$). For Proximity Prestige, the one-way ANOVA revealed a significant effect ($F(5, 48) = 3.48$, $p = 0.009$, $\eta^2 = 0.27$, High Effect). Games–Howell post hoc tests showed that strikers had significantly higher Proximity Prestige than fullbacks (mean difference = 0.094, $p = 0.007$) and central defenders (mean difference = 0.111, $p < 0.001$). For Degree Prestige, the one-way ANOVA revealed a significant effect ($F(5, 48) = 10.13$, $p < 0.001$, $\eta^2 = 0.51$, Very High Effect). Games-Howell post hoc tests showed that central defenders (had significantly higher Degree Prestige values than goalkeepers (mean difference = 0.050, $p = 0.004$), central midfielders (mean difference = 0.041, $p = 0.010$), wingers (mean difference = 0.034, $p = 0.033$), and strikers (mean difference = 0.059, $p < 0.001$).

4. Discussion

The aim of this study was to examine, with the use of social network analysis, how different tactical systems and match outcomes influence network metrics according to the playing positions of a male professional football team in the Portuguese First Division during the season of 2020–2021. It was analysed the influence of the tactical system and match outcome in different playing position on three network centrality metrics: Degree Centrality, Proximity Prestige, and Degree Prestige. As expected, central defenders, and to a lesser extent central midfielders, showed higher Degree Centrality and Degree Prestige in the 1-4-1-4-1 and 1-4-3-3 systems, although Proximity Prestige in the 1-4-3-3/1-3-4-3 favoured strikers and wingers. Conversely, our second hypothesis was not supported: in lost matches central midfielders and strikers did not emerge as the primary hubs, with central defenders remaining the most central while wingers' Degree Prestige was actually higher in wins.

4.1. Tactical Systems

Regarding the effect of tactical system across playing positions, central defenders showed higher Proximity Prestige in the 1-4-1-4-1 compared with the 1-4-3-3 tactical system. Similar findings in AS Monaco highlighted the defensive midfielder, box-to-box midfielder and the central defender were the most accessible players during the offensive sequences [12].

Across tactical systems, central defenders consistently presented higher Degree Centrality values, although central midfielders, fullbacks, and goalkeepers presented higher values compared to strikers and wingers, which are in line with other studies [27]. Central defenders are often recognised as key initiators of attacking plays. For example, an analysis of centrality variations during the 2018 FIFA World Cup identified defensive midfielders and central defenders were the most influential players in Degree Centrality [14], reinforcing that much of the passing activity originates in defensive/lower areas, particularly under conditions where players have time and space to decide [13].

Regarding Proximity Prestige, strikers exhibited higher values in the 1-4-3-3 tactical system compared to fullbacks, central defenders, and wingers. Similarly, in the 1-3-4-3 tactical system, strikers and wingers showed higher values than goalkeepers. These findings contrast a previous study that identified the defensive midfielder, box-to-box midfielder, and central defender as the most accessible players [12]. For Degree Prestige, the results are more nuanced. Strikers often attain high prestige values due to their critical positioning near the goal [12,14,19,42–44], our findings revealed that in the 1-4-1-4-1, 1-4-3-3 and 1-3-4-3 tactical systems, central defenders and midfielders presented the most significant results. These findings generally support our first expectation, which posited that central defenders and midfielders would present higher values across most network metrics in the 1-4-1-4-1 and 1-4-3-3 tactical systems. The only exception was in the Proximity Prestige metric when the team played in the 1-4-3-3 tactical system, where strikers and wingers presented higher values as mentioned before.

These findings sought the importance of having tactical flexibility. For instance, while 1-4-2-3-1 was the most used tactical system used in Spanish La Liga from 2012 to 2017 due to its versatility, 1-4-4-2 became more common between 2017 and 2021 [45]. The three tactical systems used by the team in this study likely reflected contextual adaptations, as team ranking often influences tactical system choice. UEFA Champions League and the Spanish Champion favoured the 1-4-3-3, mid-table teams used 1-4-2-3-1 and 1-4-4-2, and relegation-threatened sides often adopted five defenders' tactical systems such as 1-5-4-1 and 1-5-3-2 [45]. Given that the team analysed sought to avoid relegation, this tactical flexible may represent a deliberate reflect contextual adaptation and strategy. Overall, rigid tactical frameworks are increasingly being replaced by adaptable systems, emphasising the growing importance of flexibility in modern football [46]. Additionally, future research should consider the variation in player roles across different tactical systems. For instance, the role of a fullback in a back-four formation (e.g., 1-4-3-3) differs substantially from that in a back-three system (e.g., 1-3-4-3).

4.2. Match Outcomes

Considering the effects of match outcomes on playing position, results indicated that wingers were sensitive to team performance, exhibiting higher Degree Prestige in won matches compared to losses. This suggests that these playing positions are recognised as more influential receivers during successful performances, likely because the team exploited the width of the pitch more effectively, progressing their role in creating scoring opportunities [35].

Analysis revealed robust position-related differences in Degree Centrality, Degree Prestige, and Proximity Prestige, across match outcomes. In drawn matches, central defenders and fullbacks exhibited significantly higher Degree Centrality than wingers and strikers [18]. This may indicate a cautious build-up approach, characterised by circulation within the defensive line to search for opportunities for progression, with limited involvement from forward players.

In won matches, central defenders had higher Degree Centrality and Degree Prestige compared to the most playing positions, aligning with previous findings that central defenders and midfielders play key roles in successful tied matches [19]. These results suggest that winning teams maintain offensive organisation through controlled build-up initiated from the back. At the same time, strikers showed higher Proximity Prestige than central defenders and fullbacks highlighting their positioning in advanced zones as offensive pivots, despite their lower involvement in overall ball circulation [12].

In lost matches, central defenders again recorded the highest Degree Centrality and Degree Prestige values. This contradicts studies where midfielders, wingers, and forwards were more prominent in lost results [19]. Instead, the findings of this study indicate a style of play that focuses on control, increasing the defensive ball circulation [18]. Contrary to one of the initial expectations, Midfielders and strikers did not dominate in lost matches; rather, central defenders consistently remain as the most central actors. The contribution of central defenders to match play has increased over the years, with this position now being regarded as crucial for initiating attacking plays and, alongside central midfielders, controlling team possession [47,48], their contribution to this specific team was crucial in developing its possession-based playing style.

Despite these findings being related to one specific team, the broader patterns identified—such as the importance of central defenders in the build-up phase and the sensitivity of wingers to match outcomes—are likely transferable concepts. Their manifestation may vary based on factors like league style (e.g., English Premier League vs. Portuguese First Division), team ranking (top table teams vs. relegation zone teams) and coach philosophy; it is, therefore, recommended to take caution in generalising and interpreting the findings.

These insights offer practical guidance for coaches; for instance, tactical structures must account for both available players and managerial philosophy [20]. The fact that network cohesion can be similar across different formations [49] indicates that high centrality does not necessarily guarantee success and must be interpreted cautiously. These findings reinforce that microstructures (i.e., players) were sensitive to the influence of match outcome [18].

Furthermore, modern football must be adaptable across different tactical systems or playing positions [18,48] as, for instance, due to the increasing participation and growing importance of the central defenders and goalkeepers over time within team offensive dynamics (e.g., build-up phase) [47,48]. This variability reinforces the need to develop a playing style and coach players to perform their roles under different match contexts [18]. Coaches must be adaptable to factors like player availability and opponents, while club management must recognise that implementing an idea requires time [27,43].

4.3. Limitations and Future Research

While this study offers valuable insights, some limitations should be acknowledged. First, the analysis focused on a single team within one league and relied exclusively on passing data without incorporating positional information. Future studies integrating positional tracking and video analysis could provide a more detailed and context-rich understanding for coaches [47].

Second, only the initial tactical system at the start of each match was considered, with no account of in-game adjustments or tactical variations. Furthermore, players' positions were analysed collectively across different formations (e.g., fullbacks were grouped regardless of whether they played in a back four or back three), potentially masking formation-specific positional demands.

When analysing match outcomes, it may be more informative to consider match status and temporal segments within the match to capture variations in the network dynamics over time [18,30]. Such an approach provides a richer contextual understanding compared to analysis based solely on the final result, as team network structures often evolve throughout the course of the match.

The sample included data from only one season, which means that the results should be interpreted with caution. Future research could incorporate larger sample sizes by extending the analysis across multiple seasons (e.g., comparing one season to another) to gain a more comprehensive understanding of team dynamics and longitudinal trends over time.

Despite the increasing application of network analysis in football, there remains a lack of research at the intersection of playing positions and tactical systems. Future studies should also consider contextual variables such as match location (home vs. away) and opponent quality to better understand how player behaviours evolve throughout a season [27].

Future studies incorporating tracking data could examine not only passing connections but also spatial positioning, providing a richer understanding of how tactical systems structure player movements.

5. Conclusions

This study offers a comprehensive analysis of how tactical systems and match outcomes shape passing networks across different playing positions in professional football. A key finding was the consistent prominence of central defenders in Degree Centrality and Prestige metrics, underlining their crucial role in initiating build-up play and maintaining possession, even under unfavourable conditions. At the same time, wingers and strikers gained influence in successful performances, highlighting the situational sensitivity of the forward playing positions. The results demonstrated that tactical systems significantly influenced player involvement and connectivity, while match outcomes further modulated these patterns. Importantly, the findings revealed that there is no universal network blueprint for success; rather, performance emerges from the interaction between a team's tactical approach, player roles, and contextual match dynamics. These insights emphasise the importance of incorporating positional considerations when analysing tactical systems and highlight the value of tactical adaptability in contemporary football.

The findings of this study provide actionable insights for coaches, performance analysts, and practitioners. Recognising the central role of defenders in ball circulation can inform training design, encouraging the development of position-specific passing and decision-making skills under varying tactical systems. Coaches can utilise network metrics to identify key players in build-up phases, adapt tactical setups to maximise their influence, and anticipate how different match contexts (e.g., winning vs. losing scenarios) may alter positional contributions. For instance, understanding through network metrics which of the opponent's central defenders exerts the greatest influence during the build-up phase can assist teams in designing targeted pressing strategies to disrupt their offensive structure.

Additionally, tailoring tactical preparation to exploit or neutralise network patterns of opponents could enhance competitive performance. Overall, integrating network analysis into applied practice offers a data-driven approach to optimising tactical effectiveness and supporting informed decision-making throughout a season.

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