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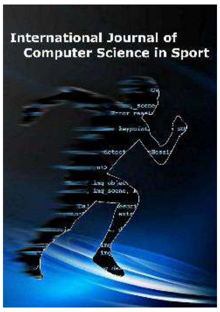

Exploring Premier League Clubs Performance and Home-Away Differences Based on Passing Network Analysis

Yang, CYY., Kolbinger, O.

Chair of Performance Analysis and Sports Informatics,

Technical University of Munich

Abstract

Whereas many studies have investigated the home advantage in football, only few studies focused on different passing patterns of home and away teams. Therefore, the aim of this study was to use two holistic indicators of social network analysis to explore potential differences: transitivity and density. As these metrics are not born in sport science, a further contribution of this study was to evaluate if these can serve as performance indicators. Based on a sample of the complete 2017/18 Premier League season, this study shows that higher ranked teams show significantly higher values for density ($Z = 12.00$; $p < .001$; $r = 0.795$) and transitivity ($Z = 7.08$; $p < .001$; $r = 0.469$) with large effect sizes. The differences of the teams' performances for home and away games were not pronounced, and only with a small effect size (density: $Z = 5.20$; $p< .001$; $r=0.267$; transitivity: $Z = 1.73$; $p = 0.084$; $r=0.089$). Overall, results contribute to the current knowledge base in two ways: First, we could show that density and transitivity are correlated with performance, which makes sense as they can be interpreted as a team's coopration variability. Second, we could show that the degree of successful collaboration is not significantly higher for matches played at home.

KEYWORDS: SOCIAL NETWORK ANALYSIS, TRANSITIVITY, DENSITY, PASSING BEHAVIOR, HOME FIELD ADVANTAGE.

Introduction

Success in football is highly dependent on the overall organization and cooperation between players (Lago-Ballesteros & Lago-Peñas, 2010), which have to work together in a dynamic and interdependent way to achieve a common goal (Ribeiro et al., 2017). Classical match analyses carried out by academics in the early years often used cumulative statistics of passes, shots, ball possession or other isolated variables to quantitatively describe the game. To then provide context for match behavior, environment-related factors, such as match location or the current score, were included in the analysis (Sarmento et al., 2018; Lago-Peñas & Lago-Ballesteros, 2011). As technology has evolved, many new analytical methods have been applied to match performance analysis, ranging from traditional multiple regression models to state-of-the-art machine learning techniques. One of the more innovative approaches are Social Network Analysis (SNA) which are based on graph theory.

The idea of social network analysis originated from investigations of social structures and functionalism by classical sociologist Emile Durkheim. In general, it refers to a set of social agents as nodes and their relationships as edges. Social actors can be any social entity, like a person, a group, or an organization. Relationship refers to how these actors are connected and how they interact, showing the dynamics between them (Wasserman and Faust, 1994). This essentially simple structure and its rich connotation make this analytical method not only emerged in the field of social sciences, but also very popular in other fields such as economics, public health, information science, etc.

In sports science, Passos et al. (2011) and Grund (2012) initially applied this method to visualize passing interactions between players in team sports, using players as nodes in a graph and passes as directed relationships between these nodes. Clemente and his team have conducted a large number of studies on the application of social network analysis in the football. First, they conducted case analysis on small sample games and pointed out that high connection number and high density characterize the degree of team cooperation (Clemente et al., 2014), and then heterogeneity and centrality of the network were also analyzed to identify the characteristics of teammate interactions during the offense (Clemente et al., 2014). Pina et al. (2017) predicts the success of the attack by building a hierarchical logistic-regression model of network indicators. Araújo lists relevant literature in detail in the chapter "variables characterizing performance and performance indicators in team sports" in his book(Araújo et al., 2017). Be inspired by them, scholars have not only regarded players as nodes to construct passing networks, but have also tried to develope the idea of considering specific areas on the field, or the combination of players and positions, as nodes to construct networks (Buldú et al., 2018). Irrespective of players or locations were use as nodes, most of the research so far focuses on using indicators such as degree centrality to mine the attributes and functions of individual nodes in the network, but lacks comprehensive explorations of network indicators describing the network as a whole.

As mentioned above, regardless of the definition of nodes, the passing network is composed of successful passes in the game, which has similar connotations to the passing and ball possession indicators favored by traditional performance analysis. Lago and Martín (2007) pointed out that inferior teams tend do have higher values in ball possession. Ballesteros and Lago-Peñas (2010) further found that the ball possession rate of teams at different ranking levels is significantly different. Even more important, several studies have shown that whether it is in the men's Premier League (Araya and Larkin, 2013) or the Women's World Cup(Kubayi and Larkin, 2020), the number of successful passes and passing accuracy of high-ranked teams is significantly higher than that of low-ranked teams. Although Clemente's team pointed out that the teams that reached different stages of the 2014 FIFA World Cup showed significant differences in density, total number of connections and clustering coefficient, suggesting connection between these network indicators and traditional performance shots metrics, the tournament sample size is small and the number of teams participating in the games varies (Clemente et al., 2015).

This makes us curious, whether metrics used to describe passing network based on successful passes comprehensively, as for example density and transitivity, have a similar measurement performance to the passing and ball possession metrics of traditional performance analysis? Density is a measure that defines the share of possible connections between two nodes in a network that are actually used, which can be used as a proxy for the offensive variability of a team. Transitivtiy goes one step further and looks for the exploited triangle structures in a network, which can be interpreted as a team's ability of providing more than one passing option at a time for each player.

In addition, the concept of "home advantage" still remains a relevant and widely debated topic in team sports match analysis. The phenomenon of home advantage is defined as "the consistent finding that the home team wins more than 50% of the games in a sporting competition with a balanced home and away arrangement "(Courneya and Carron, 1992). Because of its extreme popularity and the fact that stadiums can accommodate larger crowds, many studies have proven that home field advantage is more prevalent in football, especially compared to some individual sports (Jamieson, 2010; Legaz-Arrese et al., 2013). Numerous studies have been carried out to find out what factors contribute to home field advantage and, in general, researchers have identified three main influencing factors. Firstly, the home team is, of course, more familiar with the playing environment (Moore and Brylinsky, 1995; Neave and Wolfson , 2003). Secondly, the home team is not affected by the fatigue of travel (Ponzo and Scoppa , 2018; Van Damme and Baert, 2019). And finally, the team playing at home is supported by the crowd, which influences the performance of the visiting team as well as the referee's decisions (Pollard and Pollard, 2005; Buriamo et al., 2010).

Of course, football is a complex sport and these aforementioned factors are difficult to measure scientifically. But the COVID-19 pandemic, which started in 2020, resulted in ball games being played only in empty stadiums for longer periods of time. In this case, while the factor that away teams may suffer from travel fatigue remains unchanged, the lack of spectators could give scholars the opportunity to conduct comparative studies on home advantage. Link and Anzer (2021) believes that the players' behavior may have been influenced by tactical requirements and/or conscious or unconscious self-preservation, and that the empty stadium reduced the home advantage and reduced the referee's bias, for example in awarding fewer yellow cards to the away team. Destefanis et al. (2022) also showed that in the post-COVID season, both the offensive and defensive efficiency of away teams has increased significantly, while home teams show a very slight increase in offensive efficiency and essentially no change in defensive efficiency.

In the above-mentioned previous papers on the differences in team performance between home and away games, traditional analysis indicators such as points, goals, possession, dribbles, crosses and tackles were used to quantify team performance. To our best knowledge, none research has been conducted so far mainly to explore home and away differences in team performance in terms of network structure.

Based on the scientific gaps described above, the objective of this study is two-folded. First we want to investigate if holistic network indicators like transitivity and density are able to serve as performance indicators in football. Network density refers to the degree to which members of a network are connected to each other in their interactions. Transitivity, the network clustering coefficient, is a metric that indicates the degree of aggregation of nodes in a graph. Based on the understanding of the impact of passing behavior and team connectivity on performance discussed above, we assume that the higher the values of these metrics are, the more tactical options and opportunities a team has, the more successful is the team is. Second, we assume that teams performance differs between home and away games, leading to the following two hypotheses of this study:

H_1: Higher ranked teams have higher density and transitivity values than lower ranked teams.
H_2: The density and transitivity of teams are different between home and away games.

Methods

Sample

For our analysis, we used data from all 380 matches of the 2017/18 season of the English Premier League, provided by Stats LLC with permission for scientific studies and publication of findings. According to the reality of football matches, a team can have up to 11 players on the field at the same time. Even if substitutions are taken into account, the passing network nodes of each team are very limited. Therefore, we regard the substituted and substitute as the same node, so that the node size of the network is the same in subsequent comparisons, with only 11 players.

A total of 20 teams participated in the entire season. In the comparative test of the top 6 and the bottom 6 teams, the sample size was 228 pairs. In the comparative test of all teams between home and away games, the sample size was 380 pairs.

Applied social network analysis

Various metrics can be used to describe social networks. In the above-mentioned literature, researchers have used measures to describe individual nodes in the network, such as flow centrality and flow betweeness, while some metrics for the whole network have rarely been used in football research, such as density and transitivity.

Density refers to the ratio of the number of ties in the network to the number of theoretically possible ties(Borgatti, et al., 2018). In traditional social network analysis the more interactions between members, the more information they exchange with each other, and the more likely it is that positive emotional contagion will occur, thus having a positive impact on the overall operation of the group. In football, it refers to the number of players passing the ball to each other, divided by the number of total possible passing paths of a team. The higher the value, the closer the team's cooperation (Grund, 2012).

Transitivity, in technical terms, represents the proportion of all closed dual pathways in the network. It can be calculated using the vertex cloud set coefficient for each vertex. The vertex-clustering coefficient of a vertex is the proportion of directly connected pairs of neighbors of that vertex, out of all pairs of neighbors and is only calculated for vertices with at least two neighbors. The final metric represents a weighted average of the vertex clustering coefficients of all vertices with a point degree of at least 2. Simply put, transitivity is the the ratio of the number of triples that actually exist in the network to the number of theoretically possible triples(Borgatti, et al., 2018). In a passing network, it measures the triangular structure in the network, where a player has two passing options at a time. The more such triangle relationships in a team, the more often players have more than one passing option.

All data processing and analysis were completed through Excel and R language. The construction of passing network and indicators calculation were mainly completed using the igraph package (Csárdi et al., 2024).

Statistical Analysis

In H_1 we assume that higher values lead to better performances. So in the first step, this study will compare the density and the transitivity of passing networks of the top 6 and the bottom 6 teams of the 2017-2018 EPL final ranking. In order to verify H_2, exploring the passing network differences between home and away games, we constructed a data set of those metrics for each team facing the same opponent in home and away games, as it is shown in Table 1, to control for the opponent as a confounding variable. As data was not normally distributed, Wilcoxon signed rank tests were ran for this study, and the level of significance is 0.05. This study also calculated the effect size to measure the practical significance of the research results. Because the sample is not normally distributed, the correlation coefficient r was selected. A common interpretation of r is insubstantial when less than 0.1, between 0.1 and 0.3 for a small effect, between 0.3 and 0.5 for a medium-sized effect, and greater than 0.5 for a large effect (Cohen, 1988).

Table 1. Example of a data set used to test and compare the density of a team's home and away passing networks. Each row includes density data for a home and an away game against the same opponent.

Team	Opponent	Density Home	Density Away
Arsenal	Manchester City	4.118	3.645
Arsenal	Chelsea	4.945	3.991
Arsenal	West Bromwich	5.136	5.036
Arsenal	Manchester United	5.382	3.536
Arsenal	Brighton	5.745	4.918
Arsenal	Burnley	5.591	5.055

Results

Density

Figure 1 displays the average values of density for home and away games for each team. Visual inspection already provides indication that teams finishing in the top reach higher values then teams finishing in the bottom.

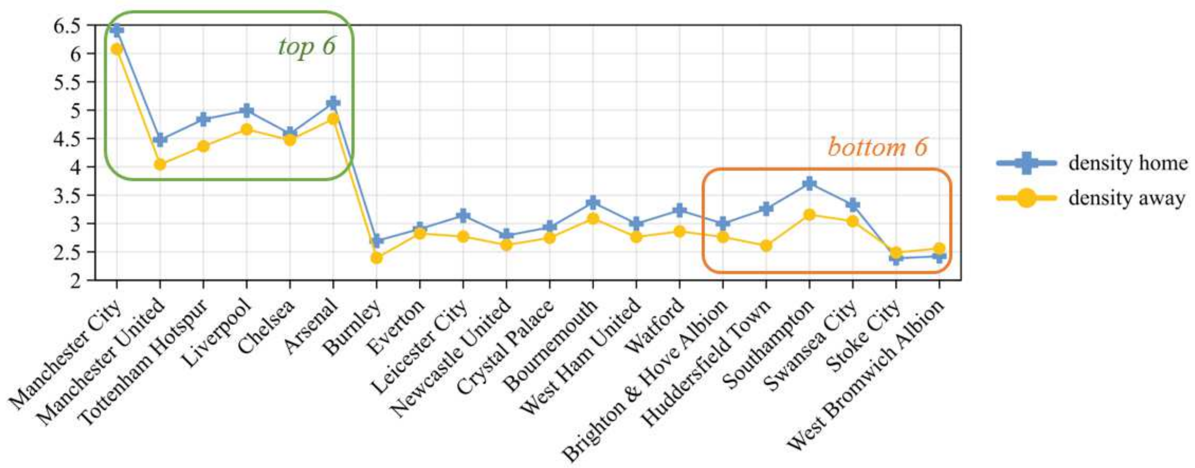

Figure 1. Comparison of home and away density averages for the 20 teams in the Premier League passing network for the 2017-2018 season. Teams are sorted based on the final ranking from left (1st) to right (20th).

In more detail, the top 6 teams of the 2017/18 season, Manchester City FC, Manchester United FC, Tottenham Hotspur FC, Liverpool FC, Chelsea FC and Arsenal FC reached a median density of 4.845 for all games of the season (figure 2). This is significantly higher ($Z = 12$; $p < .001$) compared to the bottom 6 teams including Brighton & Hove Albion FC, Huddersfield Town AFC, Southampton FC, Swansea City AFC, Stoke City FC, West Bromwich FC (median = 2.891). Effect size r is 0.795, representing a very large effect. For games played at home the teams on average reached a significantly higher median of 3.432 compared to the median for away games of 3.118 ($Z = 5.2$; $p < .001$), but only with a small effect size of 0.267.

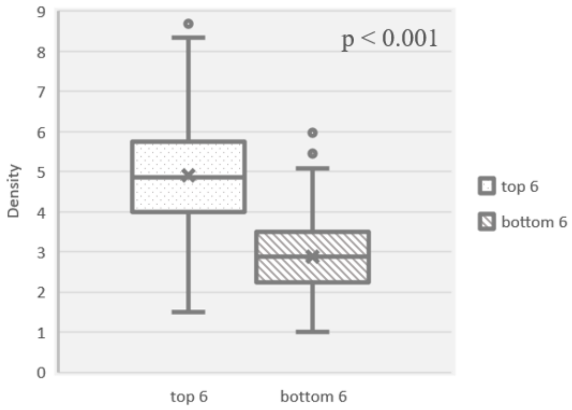

Figure 2. Box line graphs of passing network density for the top 6/bottom 6 teams and the home/away games in the Premier League for the 2017-2018 season.

Transitivity

For the transitivity, again, plotting the average values for home and away games per team, as it has been done in figure 3, already provides a good impression of the patterns for this metric. Teams from the top third of the final table reach noticeable higher values than teams from the bottom third, whereas for the difference of home and away games this difference is not as pronounced.

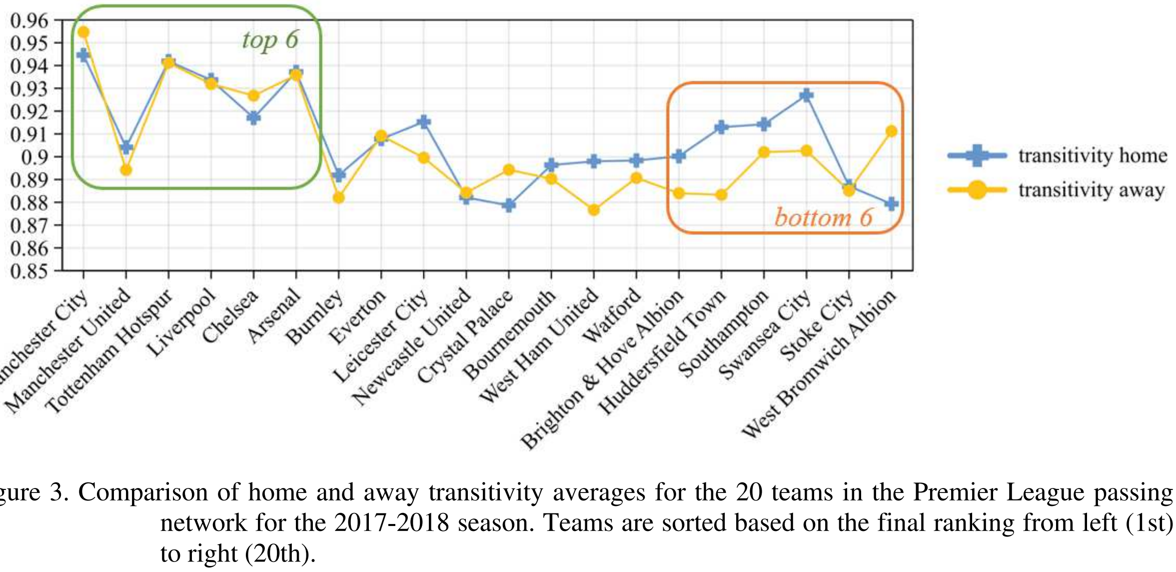

Figure 3. Comparison of home and away transitivity averages for the 20 teams in the Premier League passing network for the 2017-2018 season. Teams are sorted based on the final ranking from left (1st) to right (20th).

Accordingly, the Wilcoxon signed rank test showed significantly higher values for the top 6 teams of the 2017/18 season ($Z = 7.08$; $p < .001$) with a near large effect size ($r = 0.469$). As it can be seen in figure 4, these teams reached a median transitivity of 0.934, whereas the bottom 6 teams only reached a median transitivity of 0.910. For the comparison of the transitivity between home and away games the pattern is not as clear (figure 4). There is no significant difference ($Z = 1.73$; $p = .084$), with a slightly higher median for games played at home (medianHome = 0.915; medianAway = 0.910), but only with effect size of 0.089, which is even below the lower bound of the small effect size interval. As it can be seen in figure 3, some teams even reached higher average values for away games, whereas especially teams of the bottom half of the table often show notably lower values for away games.

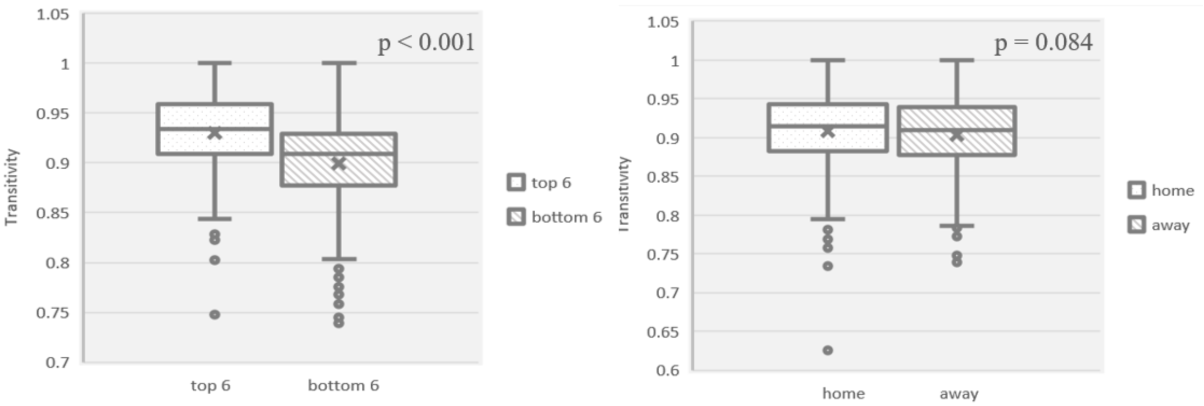

Figure 4. Boxplots of passing network transitivity for the top 6/bottom 6 teams and the home/away games in the Premier League for the 2017-2018 season.

Discussion

This study has two aims: Firstly, to explore whether two network integrity indicators can be used to measure football performance, specifically examining whether the indicators are related to team rankings. Secondly, to explore disparities of these two indicators in home and away games.The analysis results confirmed two hypotheses of this study. First, the density and transitivity of the passing network of the top 6 teams are significantly higher than that of the bottom 6 teams. Second, the density and transitivity of the passing network of the team when playing at home significantly higher than when playing away, but only with a small effect size.

As discussed in the introduction, social network analysis (SNA) methods, originating from disciplines such as sociology and graph theory, have been applied in various fields. However, their application in sports science, particularly in football research, is relatively recent and requires careful consideration due to the unique characteristics of the sport. While traditional SNA often deals with large networks, football passing networks typically involve a smaller number of nodes but with significant edge connections. Therefore, exploring the applicability of SNA methods in football research is crucial for understanding its effectiveness in this context. After conducting our study, we can confirm that not only does our research validate the feasibility of employing SNA methods in football analysis, but it also substantiates both hypotheses.

This study found that the density and transitivity of higher-ranked teams are significantly higher than those of lower-ranked teams, and their larger effect sizes also indicate that they have statistical significance worthy of reference. High density means that the entire team cooperates more closely, and high transitivity means that players have more passing opportunities, which means more tactical choices. This is consistent with other research on passing, with Grund (2016) finding that teams with higher passing rates score more goals, and other research finding that higher-ranked teams have more passes success throughout different competitions (Araya and Larkin, 2013; Kubayi and Larkin, 2020). Not only that, it is also consistent with the results of other studies on ball possession rate. A large number of previous studies have proved that different levels of teams have significant differences in ball possession rate (Carmichael, Thomas and Ward, 2001; James et al. , 2004; Lago and Martín, 2007; Ballesteros and Lago-Peñas, 2010). Same as independent indicators such as passing and ball possesion, the two overall indicators of network analysis, density and transitivity, performed good discrimination between different ranking teams in the sample of the entire Premier League season, which shows that the football passing network analysis method and the two network integrity indicators can be used to evaluate team performance.

As another finding of this study, it could be shown that density and transitivity of passing networks was significantly higher when teams played at home. As above, studies using traditional metrics such as possession rate and passing rate to investigate differences between home and way teams (Hugo et al., 2021; Bradley et al., 2014) found similar results. Gama et al. (2016) studied the number of passes and the number of passing during possession to look for home-away differences, they found out the number of passes performed by the team playing at home was considerably higher than when playing away. Zeng and Zhang (2022) pointed out except for the passing success rate in the 30 m attack area, all other pass indicators in the home matches were significantly higher than away matches on the Chinese Super League.

Compared with the test results of the two network integrity indicators and the different ranking levels of the teams in this study, their home and away difference test showed a small effect size, indicating that the difference is not that significant. Others reserchers have explored the “attenuation” of home advantage using traditional analytical metrics. Sergio (2022) found that during the COVID-19, with no audience, the offensive efficiency of home teams increased slightly, and the defensive efficiency has remained basically unchanged, using a range of offensive and defensive metrics such as possession, shots, crosses. Victor and Taha (2021) quantified home-advantage by modelling multiple seasons of Premier League data as well and found that so-called home-advantage declined to a small margin over time. Our research aligns with these studies, that the difference between home and away games appears to be non-significant based on the perspective of two overall passing network indicators.

Although we could answer our research questions, it is important to highlight some limitations to enhance the interpretation of the results. The passing network analyzed in this study is limited to successful passes only, as the data set did not include information on unsuccessful passes and their intended recipients. Besides, in the real world of football, even holistic performance indicators have to been put into context. For example some tactics will give up possession and take the form of counter-attacks to gain goals, which may not be fully captured by a passing network based solely on successful passes. Moreover, the complex factors contributing to home-field advantage may not be fully elucidated by the two passing network integrity indicators examined in this study. To address this gap, future research could explore micro-level social network analysis indicators to provide more nuanced insights into the home/away effect.

Conclusion

Overall, this study shows that two indicators that measure the entire passing network - density and tansitivity – are associated with performance and also differ between home and away matches. Social network analysis was born in graph theory and other fields, and has only recently been applied in the sports discipline. Further exploration is needed as to whether network analysis metrics can better reflect match conditions and whether they can be widely used to improve performance. As one contribution, this study adds to this process. This study contributes to a deeper understanding of the passing behaviour for home and away games, but especially between higher and lower ranked teams. From a passing network perspective, the home-away difference does exist, but is much smaller than the difference between higher-ranked and lower-ranked teams. In recent years, the turnover of players and the increase of international competitions may have led to the insignificant home field advantage, which is an interesting topic worthy of more exploration from other perspectives in the future.

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References

Antequera, D. R., Garrido, D., Echegoyen, I., López del Campo, R., Resta Serra, R., & Buldú, J. M. (2020). Asymmetries in Football: The Pass—Goal Paradox. *Symmetry*, *12*(6), 1052.

Araya, J. A., & Larkin, P. (2013). Key performance variables between the top 10 and bottom 10 teams in the English Premier League 2012/13 season. *Human Movement, Health and Coach Education (HMHCE)*, *2*, 17-29.

Bradley, P. S., Lago-Peñas, C., Rey, E., & Sampaio, J. (2014). The influence of situational variables on ball possession in the English Premier League. *Journal of Sports Sciences*, *32*(20), 1867-1873.

Buraimo, B., Paramio, J. L., & Campos, C. (2010). The impact of televised football on stadium attendances in English and Spanish league football. *Soccer & Society*, *11*(4), 461-474.

Buldú, J. M., Busquets, J., Martínez, J. H., Herrera-Diestra, J. L., Echegoyen, I., Galeano, J., & Luque, J. (2018). Using network science to analyse football passing networks: Dynamics, space, time, and the multilayer nature of the game. *Frontiers in psychology, 9*, 1900.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2018). Analyzing social networks. *Sage.*

Carmichael, F., Thomas, D., & Ward, R. (2001). Production and efficiency in association football. *Journal of sports Economics*, *2*(3), 228-243.

Carmichael, F., Thomas, D., & Ward, R. (2000). Team performance: the case of English premiership football. *Managerial and decision Economics*, *21*(1), 31-45.

Csárdi G, Nepusz T, Traag V, Horvát Sz, Zanini F, Noom D, Müller K (2024). _igraph: Network Analysis and Visualization in R_. doi:10.5281/zenodo.7682609

Cohen, J. (2013). Statistical power analysis for the behavioral sciences. *Academic press*.532.

Courneya, K. S., & Carron, A. V. (1992). The home advantage in sport competitions: a literature review. *Journal of Sport & Exercise Psychology*, *14*(1).

Castellano, J., & Echeazarra, I. (2019). Network-based centrality measures and physical demands in football regarding player position: Is there a connection? A preliminary study. *Journal of Sports Sciences*, *37*(23), 2631-2638.

Clemente, F. M., Martins, F. M., & Mendes, R. (2014). Applying Networks and graph theory to match analysis: identifying the general properties of a graph. I*n VIII Congreso Internacional de la Asociación Española de Ciencias del Deporte* (Vol. 2, pp. 587-590).

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (2014). A network approach to characterize the teammates' interactions on football: A single match analysis. *Cuadernos de Psicología del Deporte*, *14*(3), 141-148.

Clemente, F. M., Martins, F. M. L., Kalamaras, D., Wong, P. D., & Mendes, R. S. (2015). General network analysis of national soccer teams in FIFA World Cup 2014. *International Journal of Performance Analysis in Sport*, *15*(1), 80-96.

Destefanis, S., Addesa, F., & Rossi, G. (2022). The impact of COVID-19 on home advantage: a conditional order-m analysis of football clubs' efficiency in the top-5 European leagues. *Applied Economics*, *54*(58), 6639-6655.

Gama, J., Dias, G., Couceiro, M., Passos, P., Davids, K., & Ribeiro, J. (2016). An ecological dynamics rationale to explain home advantage in professional football. *International Journal of Modern Physics C*, *27*(09), 1650102.

Grund, T. U. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*, *34*(4), 682-690.

Grund, T. U. (2016). The relational value of network experience in teams: Evidence from the English Premier League. *American Behavioral Scientist, 60*(10), 1260-1280.

Santana, H. A., Bettega, O. B., & Dellagrana, R. (2021). An analysis of Bundesliga matches before and after social distancing by COVID-19. *Science and Medicine in Football*, *5*(sup1), 17-21.

Jamieson, J. P. (2010). The home field advantage in athletics: A meta-analysis. *Journal of Applied Social Psychology,* 40(7), 1819-1848.

Jones, P. D., James, N., & Mellalieu, S. D. (2004). Possession as a performance indicator in soccer. *International Journal of Performance Analysis in Sport*, *4*(1), 98-102.

Kubayi, A., & Larkin, P. (2020). Technical performance of soccer teams according to match outcome at the 2019 FIFA Women's World Cup. *International Journal of Performance Analysis in Sport*, *20*(5), 908-916.

Korte, F., Link, D., Groll, J., & Lames, M. (2019). Play-by-play network analysis in football. *Frontiers in psychology*, *10*, 1738.

Lago-Ballesteros, J., & Lago-Peñas, C. (2010). Performance in team sports: Identifying the keys to success in soccer. *Journal of Human kinetics*, *25*(2010), 85-91.

Lago-Peñas, C., & Lago-Ballesteros, J. (2011). Game location and team quality effects on performance profiles in professional soccer. *Journal of sports science & medicine*, *10*(3), 465.

Lepschy, H., Wäsche, H., & Woll, A. (2020). Success factors in football: an analysis of the German Bundesliga. *International Journal of Performance Analysis in Sport*, *20*(2), 150-164.

Legaz-Arrese, A., Moliner-Urdiales, D., & Munguía-Izquierdo, D. (2013). Home advantage and sports performance: evidence, causes and psychological implications. *Universitas Psychologica*, *12*(3), 933-943.

Maimone, V. M., & Yasseri, T. (2021). Football is becoming more predictable; network analysis of 88 thousand matches in 11 major leagues. *Royal Society Open Science*, *8*(12), 210617.

Mangiafico, S.S. 2016. Summary and Analysis of Extension Program Evaluation in R, version 1.20.05,revised2023.rcompanion.org/handbook/.(Pdfversion:rcompanion.org/documents/RHandbookProgramEvaluation.pdf.)

Moore, J. C., & Brylinsky, J. (1995). Facility familiarity and the home advantage. *Journal of Sport Behavior*, *18*(4), 302.

Neave, N., & Wolfson, S. (2003). Testosterone, territoriality, and the 'home advantage'. *Physiology & behavior*, *78*(2), 269-275.

Oberstone, J. (2009). Differentiating the top English premier league football clubs from the rest of the pack: Identifying the keys to success. *Journal of Quantitative Analysis in Sports*, *5*(3).

Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011). Networks as a novel tool for studying team ball sports as complex social systems. *Journal of Science and Medicine in Sport*, *14*(2), 170-176.

Passos, P., Araújo, D., & Volossovitch, A. (2017). *Performance analysis in team sports*. London: Routledge, Taylor & Francis Group.

Pollard, R., & Pollard, G. (2005). Venteja de ser el equipo local en fútbol: una reseña de su existencia y causas. *Rev Int Fútbol Ciencia*, *3*(1), 31-44.

Ponzo, M., & Scoppa, V. (2018). Does the home advantage depend on crowd support? Evidence from same-stadium derbies. *Journal of Sports Economics*, *19*(4), 562-582.

Pina, T. J., Paulo, A., & Araújo, D. (2017). Network characteristics of successful performance in association football. A study on the UEFA champions league. *Frontiers in Psychology*, *8*, 266057.

Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: implications for research and practice. *Sports medicine*, *47*, 1689-1696.

Sarmento, H., Clemente, F. M., Araújo, D., Davids, K., McRobert, A., & Figueiredo, A. (2018). What performance analysts need to know about research trends in association football (2012–2016): A systematic review. *Sports medicine*, *48*, 799-836.

Lago, C., & Martín, R. (2007). Determinants of possession of the ball in soccer. *Journal of sports sciences*, *25*(9), 969-974.

Link, D., & Anzer, G. (2021). How the COVID-19 pandemic has changed the game of soccer. *International Journal of Sports Medicine*, 83-93.

Van Damme, N., & Baert, S. (2019). Home advantage in European international soccer: which dimension of distance matters? *Economics*, *13*(1).

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications.

Zeng, Y., & Zhang, H. (2022). Analysis of influencing factors of passes in the chinese super league. *BMC Sports Science, Medicine and Rehabilitation*, *14*(1), 1-10.