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Successful team synergies. A Social Network Analysis on high performing soccer teams in the UEFA Champions League.

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Resumo

A interacção sinergética entre colegas de uma equipa de futebol tem propriedades susceptíveis de serem estudadas através da Social Network Analysis (SNA). A análise de redes formadas pelos passes de colegas de equipa tem demonstrado que o sucesso colectivo está correlacionado com alta densidade de rede e coeficientes de clustering, bem como com centralização de rede reduzida. Apesar disso é importante evitar uma simplificação excessiva no estudo deste fenómeno, nomeadamente a consideração por igual na obtenção das métricas de rede dos eventos que estão na origem quer da performance colectiva de sucesso quer de insucesso. No presente estudo, investigamos se a densidade, o coeficiente de clustering e a centralização das redes podem prever o sucesso ou o insucesso da performance de uma equipa no futebol. Analisámos 12 jogos do Grupo C da UEFA Champions League 2015/2016, utilizando registos públicos das transmissões de TV. Realizaram-se análises de notação para categorizar as sequências ofensivas como bem-sucedidas ou mal-sucedidas e para recolher os dados das redes de passe e subsequentes métricas. Utilizou-se um modelo de regressão logística hierárquica para prever o sucesso das sequências ofensivas a partir da densidade, do coeficiente de clustering e da centralização das redes, utilizando a variável total de passes como variável moderadora. Os resultados confirmaram o efeito independente das métricas de rede. A densidade, ao contrário do coeficiente de clustering e a centralização, foi um preditor significativo do sucesso das sequências ofensivas, tendo-se registado uma relação negativa entre densidade e sucesso de sequências ofensivas. Para além disso, densidades reduzidas foram associadas a um número superior de sequências ofensivas, embora maioritariamente mal-sucedidas. Por outro lado, altas densidades foram associadas a um número inferior de sequências ofensivas bem-sucedidas, mas também a um menor número total de sequências e de "perdas de posse de bola" sem que a equipa atacante tivesse conseguido entrar na zona de finalização. Uma análise individual por equipa indicou que a relação entre a performance da equipa e a densidade é dependente da equipa. A aplicação de SNA aos desempenhos de sucesso e insucesso, de forma independente, de uma equipa de futebol é importante para minimizar uma possível simplificação excessiva das sinergias efectivas de uma equipa.

Palavras-chave: social network analysis, jogos desportivos colectivos, futebol de elite, análise de jogo, performance de peritos, sinergia de equipa

Abstract

The synergistic interaction between teammates in soccer has properties that can be captured by Social Network Analysis (SNA). The analysis of networks formed by team players passing a ball in a match shows that team success is correlated with high network density and clustering coefficient, as well as with reduced network centralization. However, oversimplification needs to be avoided, as network metrics events associated with success should not be considered equally to those that are not. In the present study, we investigated whether network density, clustering coefficient and centralization can predict successful or unsuccessful team performance. We analyzed 12 games of the Group Stage of UEFA Champions League 2015/2016 Group C by using public records from TV broadcasts. Notational analyses were performed to categorize attacking sequences as successful or unsuccessful, and to collect data on the ball-passing networks. The network metrics were then computed. A hierarchical logistic-regression model was used to predict the successfulness of the offensive plays from network density, clustering coefficient and centralization, by using the number of total passes as a moderator variable. Results confirmed the independent effect of network metrics. Density, but not clustering coefficient or centralization, was a significant predictor of the successfulness of offensive plays. We found a negative relation between density and successfulness of offensive plays. However, reduced density was associated with a higher number of offensive plays, albeit mostly unsuccessful. Conversely, high density was associated with a lower number of successful offensive plays, but also with overall fewer offensive plays and "ball possession losses" before the attacking team entered the finishing zone. An individual team analysis indicated that a relationship between team performance and density is team dependent. Independent SNA of team performance is important to minimize the limitations of oversimplifying effective team synergies.

Keywords: social network analysis, team sports, elite soccer, match analysis, expert performance, team synergy

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Introduction

In today's society it is widely recognized the importance of teams in many areas of our daily lives (Duch, Waitzman, & Amaral, 2010). The team, rather than the individual, has become the basic work unit in many activities and organizations (Balkundi & Harrison, 2006), and team sports are excellent examples revealing the importance of team dynamics for success (Duch et al., 2010).

A team is a group of individuals working cooperatively and in a coordinated way to achieve a common goal (Zaccaroa, Rittmana, & Marks, 2001). Team performance is more than the sum of the interdependent individual performances, as individuals strive to coordinate between different roles and tasks (Anderson & Franks, 2001). In team sports performance individual players in a successful team act as a coherent unit, thus creating a team synergy (Araújo & Davids, 2016).

Individual and collective behavior has been intensively studied in team sports performance analysis. The behavior of an individual player affects the team's behavioral pattern (Vilar, Araújo, Davids, & Button, 2012), and conversely, teammates may influence the behavior of each individual player.

Team Sports Analysis Literature Review

There is no way of denying the great influence of the spatial and temporal interactions established by players and teams on team sports. Primary types of spatio-temporal data captured from team sports are the ones which basically allow us to know what, where and when events happen. Movement data describes where a player, or the ball, is located at a specific moment, whereas event data specifies which relevant actions happen during a match (Stein et al., 2017). Trajectories of players and objects (e.g., ball) can be captured on two ways: a) processing the images of fixed cameras used by optical tracking systems; b) using device tracking systems based on GPS or RFID attached to players' clothes or embedded in the ball. Event data is mostly of two types: player events (e.g. passes and shots) and technical events (e.g. fouls, time-outs and start/end of period). These data may be obtained in part from the trajectories of the players or be directly captured using video analysis too. Movement and event data play a complementary role in team sport analysis and are the primary input used by the models and techniques described subsequently (Gudmundsson & Horton, 2016).

The great diversity of existing techniques is, in our view, the consequence of three main aspects. The first is the way information is captured, with technological advance and increasing influence of engineering on issues such as the placement of sensors or the use of drones in the capture of images. Secondly, this kind of data allows innumerable possibilities of study, always guided by theories and approaches of sports science. Such studies resulted in the expression of the phenomena through several indices and composite variables linked to individual and collective performance. These methods and variables are described in the next sub-section (Individual / collective indices and composed variables). Finally, and more recently, the proliferation of contributions and interactions between this area of knowledge and others, such as biology or computational science, combined with the increasing ability to capture and store large amounts of data, has originated new methodologies and perspectives on how to compute and analyze team sport data (data mining, information visualization and visual analytics), This issue will be discussed in subsequent sub-sections.

Individual / collective indices and composed variables

According to Araújo et al. (2015), individual behavior in a team is constrained by several factors, such as the player's position in the field (in relation to the other teammates and opponents), strategic and tactical intents, playing phases (i.e., attacking and defending), game rules, etc. This perspective is corroborated by Stein et al. (2017), for whom the restriction of movement by a pitch and rules, driven by the predetermined objective, and influenced by the movement of own and opposing team players, is a big challenge when team data is analyzed. Consequently there are several techniques for capturing individual behavior that meet spatial criteria. One of the earliest works was done by Grehaigne (1988), who defined the playing area of each player, by recording their positions in the field every 30 seconds, according to a previous subdivision of the field into 40 equal squares. This work was a predecessor of many studies, and the division of playing area has been reported as a useful first step for a diversity of methods in behavior analysis in sport. About this topic, Gudmundsson and Horton (2016), in a survey on spatio-temporal analysis on team-sports, highlighted the intensity matrices and dominant regions.

The existing studies of intensity matrices differ in the way the playing area was divided and the type of events studied. Several authors have divided playing area into rectangles of equal sizes (Bialkowski A. , Lucey, Carr, Yue, Sridharan, & Matthews, 2014; Borrie, Jonsson, & Magnusson, 2002; Lucey, Bialkowski, Carr, Foote, & Matthews, 2012; Shortridge, Goldsberry, & Adams, 2014; Takuma, Yamamoto, & Yamazaki, 2014). However, the truth is that individual athletes' behavior is not subordinated to any symmetrical geometric logic, but rather to the relationships between players and their teammates, opponents, game objects (e.g. ball positioning) and game targets (e.g., goal, basket). Taking this into account, researchers have established spatial discretization from predefined assumptions of the players behavior, such as subdivisions into areas aligned with the penalty box in soccer (Camerino, Chaverri, Anguera, & Jonsson, 2012) or considering the relative position of the players to the three-point line and the basket, as well as the expert intuition about shooting in basketball (Goldsberry & Weiss, 2013; Maheswaran et al., 2014). Another approach regarding the subdivision of the playing area is the polarization of the playing area, assuming that the behavior of the athletes is similar in locations equidistant to the goal or basket (Maheswaran, Chang, Henehan, & Danesis, 2012; Reich, Hodges, Carlin, & Reich, 2006; Yue, Lucey, Carr, Bialkowski, & Matthews, 2014). All these spatial discretization techniques allow producing intensity matrices by counting events that occur in each region previously created. Maheswaran et al. (2014) studied the regions visited by the players by extracting the location points from the trajectories of the players, while Bialkowski, Lucey, Carr, Yue, and Matthews (2014) performed a similar investigation on soccer, registering passes and touches made by the players in each region. Other authors went beyond the discrete spatial distribution of players location during the match, and obtained matrices of intensity for the shots (Franks, Miller, Bornn, & Goldsberry, 2015; Goldsberry & Weiss, 2013; Maheswaran et al., 2012; Reich et al., 2006; Shortridge et al., 2014) and passes (Borrie et al., 2002; Camerino et al., 2012; Cervone, D'Amour, Bornn, & Goldsberry, 2014; Takuma et al., 2014) performed in each region.

Another technique reviewed by Gudmundsson and Horton (2016) within the framework of spatial discretization is the dominant region. The method was introduced by Taki, Hasegawa, and Fukumura (1996). A player’s dominant region is the set of spatial points (area) that this player can reach before anyone else. In its simplest form, in which acceleration is not considered, dominant regions are equivalent to Voronoi cells (Fortune, 1987). Fonseca, Milho, Travassos, and Araújo (2012) considering the minimum distance between two teammates and the size of players dominant regions, observed that the size of the dominant region was higher for the attacking team and that the behavior of the defending team is more unpredictable. In a different study, Ueda, Masaaki, and Hiroyuki

(2014) compared the team-area (the smallest enclosing orthogonal box containing all the field players of the defending team) with the dominant region, during the two phases of the game: attack and defense. The dominant regions of successful attacks were thinner than those of unsuccessful attacks. It was concluded that the dominant region is closely linked to offensive performance, so it may be possible to evaluate the performance of a group of players using the dominant region. In this respect it is very important to refer the motion model developed by Taki and Hasegawa (2000), who attempted to overcome research limitations already reported by Gréhaigne, Bouthier, and David (1997), in particular as regarding the validity of the assumption that all space inside a Voronoi cell is reachable in a shorter time by its designated player. Gréhaigne et al. (1997) considered that in order to accurately define points in space where a player could arrive before anyone else, it would be important to take into account the position, speed, acceleration and movement direction of the players.

Several other researchers applied the same concept of dominant region as support for other methods and metrics. Perhaps the one that is more conceptually linked to the dominant region is the team's dominant region, resulting from the union between all dominant regions of each of the team players. Variations in the size of this area were indicated as indicators of collective performance (Taki, Hasegawa, & Fukumura, 1996). Other authors have considered useful to weight the dominant regions of the players according to the distance to the opponent's goal and/or the ball, in order to better express the contribution of the players to the team performance (Fujimura & Sugihara, 2005). Another metric already explored in this field is the player's passable area, which is the region where the player can potentially receive a pass (Fujimura & Sugihara, 2005; Taki & Hasegawa, 2000). This concept is closely linked to the dominant region, since it is considered that the player is available to receive a pass when it is possible to determine a reasonable direction and speed of pass, such that the same player can intercept the ball before anyone else. However, the existing tools only allow considering as pass trajectory the shortest path between two players and the speed of the ball as a constant. It is important to develop more realistic models taking into account other trajectories (e.g. aerial, ball-spin) and variable ball speeds. Another promising topics derived from concept of dominant region are the spatial pressure applied by one team over the other (Taki, Hasegawa, and Fukumura, 1996) or investigation on player's rebounding performance (Maheswaran, 2014) using the concept of Voronoi diagram, more concretely.

The collective coordination of a team has been captured by specific group-based measures, too. One of the most studied aspects is the team's center or centroid that is obtained by computing the mean lateral and longitudinal positional coordinates of each player in a team (Araújo, Silva, & Davids, 2015) and represents the relative positioning of both teams in forward-backward and side-to-side movement displacement. Frencken, Lemmink, Delleman and Visscher (2011) in a study of inter-team coordination in small-sided games observed that in many plays that ended in goal there was a cross between the centroid of the attacking team and the defending one. On the other hand Bartlett, Button, Robins, Dutt-Mazumder, and Kennedy (2012) have reported that in 11 versus 11 soccer a clear convergence of the centroids of the teams in the plays that resulted in goal was not observed. Thus, the relationship between the cross of team's centroids and the creation of goal opportunities remains to be confirmed. Still in the analysis of team's centroid, Clemente, Couceiro, Martins, Mendes, and Figueiredo (2013) considered the centroid of the team according to the distance of each player to the ball, in the attempt to determine its influence in the plays. The authors reported large lateral oscillations of the team's weighted centroids, which were interpreted as a result of the effort of the attacking teams to destabilize the opposing defensive organizations by varying the attack corridor.

Among the aspects of team coordination more commonly studied in team sports research is spatial dispersion of players on field. This is expressed by variables such as stretch index, team spread or effective playing space (Araújo & Davids, 2016). The stretch index measures the degree of expansion / contraction of occupied space lateral and longitudinally by a team throughout the game, by computing the mean of the distances between each player and the team's centroid. This index can be a radial measure or it can be calculated according to the axis expansion, providing different measures of longitudinal and lateral dispersion (Araújo, Silva, & Davids, 2015). Thus, the stretch index represents the mean deviation of each player from the spatial center (Bourbousson, Sève, & McGarry, 2010). Investigation on this topic has demonstrated the intermittent expansion and contraction patterns of competing teams in soccer and basketball, according to attacking and defending phases (Araújo, Silva, & Davids, 2015). In the work of Clemente, Couceiro, Martins, and Korgaokar (2012), the distances of the players to the pondered centroid were considered to calculate the stretch index, obtaining a stretch index that is also weighted. The results indicated a negative relationship between the stretch index values of the opposing teams, as well as lower values of the metric at times when the team did not have possession of the ball, compared to the values registered with possession of the ball.

Another dispersion measure that was reported by Moura, Martins, Anido, Barros, and Cunha (2012) is team spread, which is calculated as the square root of sums of the squares of the distances between all pairs of players not considering the goalkeeper. Authors observed a counter-phase relationship between expansion and contraction in defense, as well as greater dispersion values when teams were attacking.

The effective playing space, which in the study of Ueda et al. (2014) was compared to the dominant region in both phases of the game - offensive and defensive, provides information on how the teams are stretched across the field. This information has been used by the authors, in a similar way to the studies of the last two mentioned metrics, to differentiate the moments in which the teams have the possession of the ball from the moments in which it does not (Frencken & Lemink, 2008). However Bartlett et al. (2012) state that the relation between measures of team dispersion and the defensive and offensive phases of the game is uncertain.

Finally, as team behavior is a collective organization that emerges from the cooperation between teammates (Gréhaigne, Bouthier, & David, 1997; Peña & Touchette, 2012), the emergence of such collective behaviors can be assessed and understood through the measurement of key synergistic properties such as degeneracy, i.e., the structurally different components that perform a similar (but not necessarily identical) function in a given context (Araújo & Davids, 2016). The degeneracy of team behavior as a social relationship property can be captured by Social Network Analysis (SNA) (Grund, 2012; Peña & Touchette, 2012). SNA has been applied to soccer (Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2014b), in particular to analyze ball-passing networks in a team. Later, in the section about SNA on soccer, this issue will be resumed.

Data Mining

Team sport analysis is a growing research field that has experienced problems in dealing with increasingly larger and more complex datasets. Data mining, which is a step in the process of knowledge discovery in databases that consists of applying specific algorithms in order to extract patterns (or models) on these data, has been very useful to deal with such problems, According to Fayyad, Piatetsky-Shapiro and Smyth (1996) the two main goals of data mining are prediction, which involves using some variables or fields in the database to predict unknown or future values of other variables of interest; and description, which focuses on finding patterns interpretable by humans that describe the data. There are a variety of data mining techniques used to analyze large and complex datasets, with possible application to team sports data (Gudmundsson & Horton, 2016; Stein et al., 2017). Clustering is the grouping of objects that are more similar to each other than to those in other clusters, regardless of the definition of similar that may be established. According to Gudmundsson and Horton (2016) it's possible to apply one of the clustering algorithms created by Lee, Han, and Whang (2007) to identify common movement patterns of individual or groups. More specifically this technique has been used to find common behavioral patterns of individual players in soccer (Janetzko et al., 2014).

Another data mining technique is classification, which according to Fayyad et al. (1996) is the process of "learning a function that classifies a data item into one of several predefined classes". This technique was successfully applied to detect dangerous situations in soccer, defined by the "shot on goal" criteria (Stein et al., 2015). Classifiers were firstly trained with several features that occurred shortly before the shot on goal and then they were applied on the data, which allowed to detect potentially dangerous situations, as well as periods where did not occur any shot on goal but whose feature values were similar to previously trained data.

Regression is used when one intends to estimate the relationship between dependent and independent variables. This relationship is expressed in a function that can predict, with greater or less accuracy, future observations. Lucey, Bialkowski, Monfort, Carr, and Matthews (2014) have studied the offensive performance in soccer, having proposed a model, based on logistic regression, to estimate the probability of shooting succeed. This model determined that factors such as the game phase in which the shot has occurred, the defender proximity to shooter, the interaction of surrounding players, the speed of play and the shot location have a relevant effect in determining the likelihood of a successful shot. In another example, studying defensive performance in basketball, more specifically rebounding, Maheswaran et al. (2014) used linear regression to compute metrics for player's hustle and conversion, two of the three components (positioning was the other one) of authors' decomposition of rebound. The results have reported that the top-ranked players in these metrics were those who were also considered by experts as the best performers.

Another group of data mining techniques is summarization. Several techniques, some more complex than others, are used in order to find a compact description of the data (Stein, 2017; Fayyad, Piatetsky-Shapiro, & Smyth, 1996). Among the simplest techniques is the calculation of the mean and standard deviation or the dimensional reduction. Examples of more complex summarization techniques include, for example, clustering and the determination of centroids as representative elements of clusters, a technique widely used in team sports analysis and discussed earlier. Another relevant example is the work of Perin, Vuillemot, and Fekete (2013), which offers compact yet expressive standard visualizations of soccer phases.

Change and deviation detection and dependency modeling, respectively used in the detection of outliers and in the identification of significant relationships between variables, can also be interesting methods to team sport analysis. According to Stein et al. (2017) change and deviation detection can be used to identify players whose performance distinguishes, positively or negatively, from that of other players, while dependency modeling can be applied to identify events that occur in the condition of other relevant events take place, such as a goal scored or conceded.

Information Visualization

Information visualization is a recent and growing research field that has developed useful tools for the communication of information obtained from spatiotemporal datasets. These techniques may be very useful when exploring a dataset in search of insights as interesting patterns and descriptive features (Fekete, van Wijk, Stasko, & North, 2008; Stein, 2017). Among the examples of techniques we find in sport are statistical techniques such as the presentation of scatter plots or parallel coordinate plots or more sophisticated and specialized techniques such as today's so-called live-covers of sporting events made online which offer textual descriptions of key events in real-time as well as graphs with different type of information about players or teams. One of the most common approaches is the use of heat maps, which are intuitive, simple to obtain and very versatile. There are many examples on literature applied to different sports, such as an attempt to discover the best shooters in the NBA by visualizing the spread and range of shooters (Goldsberry, 2012); a similar work in ice hokey visualizing the shot distances using radial heat maps (Pileggi, Stolper, Boyle, & Stasko, 2012); and the work of Silva et al. (2014) on youth soccer, who has observed that more skillful players displayed higher spatial unpredictability compared to less-skilled players on the smaller fields, but not on larger fields, where levels of predictability were identical for both groups. Recently, Perin et al. (2013) has developed a system of visual exploration of phases in soccer, using various visualization tools such as a passing network, time line and sidebars for various detailed information, allowing multiple comparisons between players, teams and further examination of the phases of a game.

Visual Analytics

Visual analytics methods, characterized by their interdisciplinary, can combine several research areas such as data mining and visualization, among others, thus consisting on the combination of automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making from the study of large and complex data sets (Keim et al., 2008). This integrative character of visual analytics allows researchers of different research areas, such as team sport, to contribute with their specific knowledge during the analysis process (data mining) to obtain immediate specialized visual feedback of the results (visualization) (Stein, 2017).

Match Analysis on Soccer Literature Review

The unique nature of soccer, with the constant flow of the ball and few scores, especially when compared with other sports, makes simple statistics such as the number of assists or scored goals being inadequate as collective or individual performance measures. Fortunately this situation has changed and in recent times, especially since the UEFA Euro Cup 2008, a number of unprecedented statistical information in soccer has been made available for analysis. Obtaining and publishing a significantly higher amount of statistical data allows a more detailed analysis of the phenomenon, as testifies the proliferation of match analysis applied to soccer in last decades (Peña & Touchette, 2012).

Sarmento et al. (2014) proposed to classify studies on match analysis depending on the type of analysis performed in: descriptive, comparative and predictive analysis. Descriptive research has been mainly focused on measuring the physical demands, through methods like kinematic and notational analyses (Bradley, Di Mascio, Peart, Olsen, & Sheldon, 2010; Di Salvo et al. 2007; Gregson, Drust, Atkinson, & Di Salvo, 2010; Vigne, Gaudino, Rogowski, & Alloatti, 2010). At the same time some researchers have done comparative studies, associating the performance level with different variables like playing position (Barros et al., 2007; Bloomfield, Polman, & O'Donoghue, 2007; Dellal et al., 2011; Di Salvo et al., 2010; Rampinini, Coutts, Castagna, Sassi, & Impellizzeri, 2007), competitive level (Hughes & Franks, 2005; Lago-Ballesteros & Lago-Peñas, 2010), game result, quality of opposition and match location (Castellano, Blanco-Villaseñor, & Álvarez, 2011; Lago & Martín, 2007; Lago-Peñas & Dellal, 2010; Taylor, Mellalieu, James, & Shearer, 2008). For many years match analysis research has focused on kinematic analysis or notational analysis (Clemente, Martins, Kalamaras, Wong, & Mendes, 2015), enabling the general description of technical, tactical and physical variables as an attempt to quantify the activity of players.

Despite of the importance of descriptive and comparative research, by the beginning of this century one of the main critics in literature used to be the need to move beyond the description of behaviors and progress towards prediction of performance (Sarmento et al., 2014; Gréhaigne, Mahut, & Fernandez, 2001). Another frequently pointed research limitation has been the fact that studies were being done disregarding situational and interactional contexts in which such performances had happen (Sarmento et al., 2014). Subsequently, over the last few decades there has been increasing interest in identifying and classifying teams and their properties (Araújo, Silva, & Davids, 2015; Clemente, et al, 2015). Having this on mind some researchers on match analyses have tried to find associations of cause/effect in different interactional situations, having the aim to determine the most effective ways of playing. The relevance of this kind of studies is generally recognized, since match analysis has played a relevant role in improvement of sports (Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2014) and has allowed the development of new methods to analyze the team's behavior, in order to measure the tactical and collective performance (Duarte et al., 2012). Thus, research on match analysis has evolved from studies that considered athletes as independent and autonomous units to studies in which the main focus is the relationship between individuals in a given context (Lusher, Robins, & Kremer, 2010).

Social Network Analysis in Soccer

SNA has been applied on soccer at different levels: i) micro- analysis on and individual level; ii) meso-analysis on the players' contribution for the team performance; and iii) macro-analysis on global interaction of the team (Clemente et al., 2014b). On the past few years several studies have explored these three levels of analysis with different approaches and different objectives. One of the common purposes of many studies is the identification of methods and metrics in order to identify the properties of the connection between players in the network (Clemente et al., 2014b), and thus finding a "quantifiable representation of a team's style using network theory" (Peña & Touchette, 2012).

These studies demonstrated that some metrics are useful to characterize styles of play and cooperation among teammates (Cotta, Mora, Merelo-Molina, & Merelo, 2011), as well as the relation between individual actions and team tactical behavior (Passos et al., 2011). Centrality metrics have been used to identify the most influential tactical positions within a team. For example, by analyzing the in-degree and out-degree centrality of the Portugal national soccer team players, Mendes, Clemente and Martins (2015) found that during the FIFA World Cup 2014 the central midfielders were the key players in the attacking-building process. A similar study examining degree centrality and degree prestige of Switzerland national team players during the same competition showed that the key players receiving the ball were also the midfielders, suggesting this team has a style of play based on attacking building (Clemente, Martins, Kalamaras, Oliveira, Oliveira, & Mendes, 2015b). Thus, network metrics such as density, heterogeneity and centralization are effective for characterizing the cooperation between players (Clemente, Couceiro, Martins, & Mendes, 2015a). More recently it was compared the importance of each tactical position to build the offensive process of national teams participating in the 2014 FIFA World Cup. Similarly, it was found that central midfielders are the most influential players in attacking process of most teams. These results were obtained from an analysis of out-degree, in-degree, closeness and betweenness values of participating players on competition (Clemente, Martins, Wong, Kalamaras, & Mendes, 2015d). Finally, in a study by Duch, Waitzman and Amaral (2010) that characterized the performance of the players at UEFA Euro 2008, it was proposed a measure of individual and collective performance, flow centrality - "the betweenness centrality of the player with regard to the opponent's goal". It has been noted that the metric provides sensible results, in agreement with the subjective views of analysts and spectators.

Analyses of network heterogeneity and centrality reveal that team offensive play has many variations and short patterns that increase collective unpredictability (Clemente et al., 2014b). Furthermore, high total links and high density can convey the team’s greater ability to pass the ball between all players and to function as a whole, as well as to decentralize the network (Clemente, Martins, & Mendes, 2014a). For example, a study analyzing team ball-passing networks in 760 matches of the English Premier League (Grund, 2012) showed that high levels of network intensity were associated with increased team performance (goals scored), and centralized interaction patterns with decreased team performance. More recently, similar research analyzing ball-passing networks of teams competing at the FIFA World Cup 2014 (Clemente F. M., Martins, Kalamaras, Wong, &

Mendes, 2015c) revealed significant differences in density, total links and clustering coefficient between teams reaching different stages of the competition. These findings further demonstrate an association between higher density, total links and clustering coefficient with performance variables such as goals scored, overall shots, and shots on goal (Clemente et al., 2015c).

Aim

Despite these recent advances, research in the field has remained focused on the association between ball-passing network metrics and coarse-grained team performance variables (e.g. goals scored, shots, shots on goal, or competition stage reached) (Grund, 2012; Clemente et al., 2015c), which implies that team performance outputs and network properties metrics are measured simultaneously (Grund, 2012). However, since ball-passing network analysis offers an overall picture of events occurring during a certain period of time, typically a synthesis of several complete matches, the events leading to successful or unsuccessful team performance are included in the same analyses. Thus, it remains unknown whether specific network properties and successful (or unsuccessful) team behavior are associated. Furthermore, although previous research based on ball-passing networks suggests that high density (Clemente et al., 2015c) and low centralization (Grund, 2012) are associated with successful teams, the relation between clustering coefficients and team performance is more uncertain (Peña & Touchette, 2012; Gudmundsson & Horton, 2016). Thus, the aim of this study was to test whether team network density, centralization and clustering coefficient can be used to predict the outcome of offensive plays. Finally, we also studied if the characteristics that lead to team success in offensive plays in soccer were conspicuous in the performance of each high-level team, i.e., more than a style of play of a team, we tested if these characteristics are indicators of successful play of any high level team.

Method

Sample

The choice of the sample for the study was based on some important assumptions. Firstly it was a central concern that the collective processes express, as far as possible, the training stimuli. Taking this into account, this study deliberately focused on club-teams rather than on national teams because club-teams train and compete together for longer consecutive periods of time. We analyzed the 12 games of the Group Stage of the UEFA Champions League Group C of 2015/2016 season. The four teams analyzed were Club Atlético de Madrid (CAM); Football Club Astana - Астана Футбол клубы (FCA); Galatasaray Spor Kulübü (GSK) and Sport Lisboa e Benfica (SLB).

Procedures

Our analysis focused on collective offensive processes. Offensive play is a set of attacking actions performed by a team between recovering and losing ball possession. According to Garganta (1997) a team is in possession of the ball, and therefore in attacking process, when any of its players respect, at least, one of the following conditions: i) holds at least two consecutive contacts with ball, ii) performs a positive pass (allowing the maintenance of ball possession), and iii) performs a shot (finishing). We considered that a team is in possession of the ball when it performs a positive pass, i.e., it maintains ball possession after the pass.

The video footage used in the analysis was obtained from TV broadcasters. We started by categorizing all offensive plays as *successful* when the attacking team entered the *finishing zone*, which was previously reported as a proxy variable for scored goals when measuring successfulness in soccer (Tenga, Ronglan, & Bahr , 2010). The concept of finishing zone was based on Gréhaigne et al's longitudinal division of the soccer field into four equal areas (Gréhaigne et al., 2001). These areas are designated according to the direction of the attack as follows: defensive zone, pre-defensive zone, pre-offensive zone and offensive zone. The offensive zone in elite soccer was defined as the finishing zone (Lago, Lago, Rey, Casáis, & Domínguez, 2012) (see Figure 1).

Successful offensive plays (SOPs) include plays that finished with a shot at the goal and those where the team retained ball possession until entering the finishing zone.

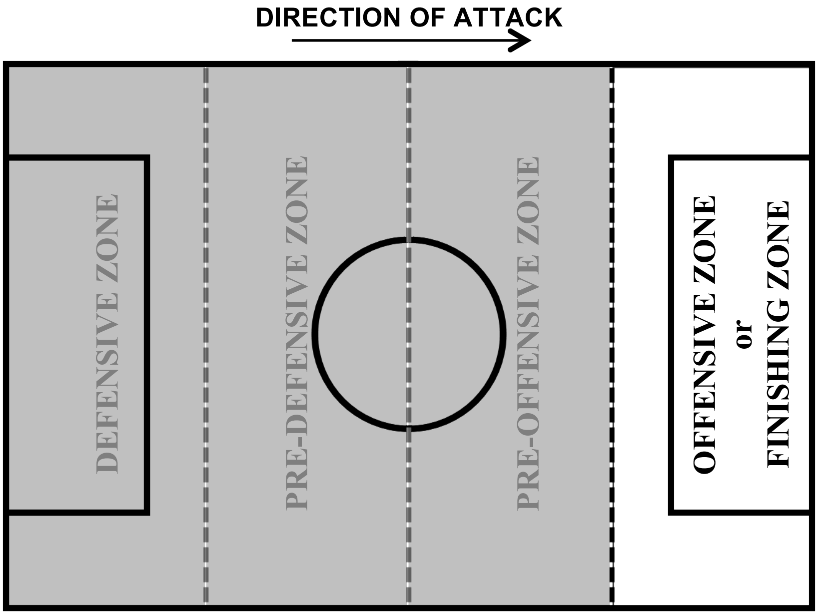


Figure 1. Longitudinal division of football field for definition of finishing zone.

Unsuccessful offensive plays (UOPs) were all the plays where the team lost ball possession without meeting either of the SOP criteria. *Neutral plays* were offensive plays where a team did not lose ball possession but also did not meet the SOP criteria. This neutral category included all offensive plays that were initiated: (i) from an offensive corner kick; (ii) in an offensive throw-in; and (iii) from offensive free kicks with a first pass directly into the finishing zone. The neutral offensive plays were not included in the present analysis.

The offensive plays were identified and categorized with *Longomatch* software from every pass performed in the 12 matches. The players who passed and received the ball were registered for each offensive play. A number from one to 11 was assigned to each player according to his initial position within the team's tactical system. The same number was assigned to players performing the same tactical position. Taking into account their different stoppage times, each half of the match was divided into three fractions with the same duration. Next, two adjacency matrices of offensive plays (successful and unsuccessful) for each opposing team were created for the six periods of the match, in a total of 24 adjacency matrices per match (see Figure 2). Each of these adjacency matrices was then imported to the software *NodeXL* to compute the networks and their metrics. All statistical procedures were performed using *SPSS Statistics 24*.

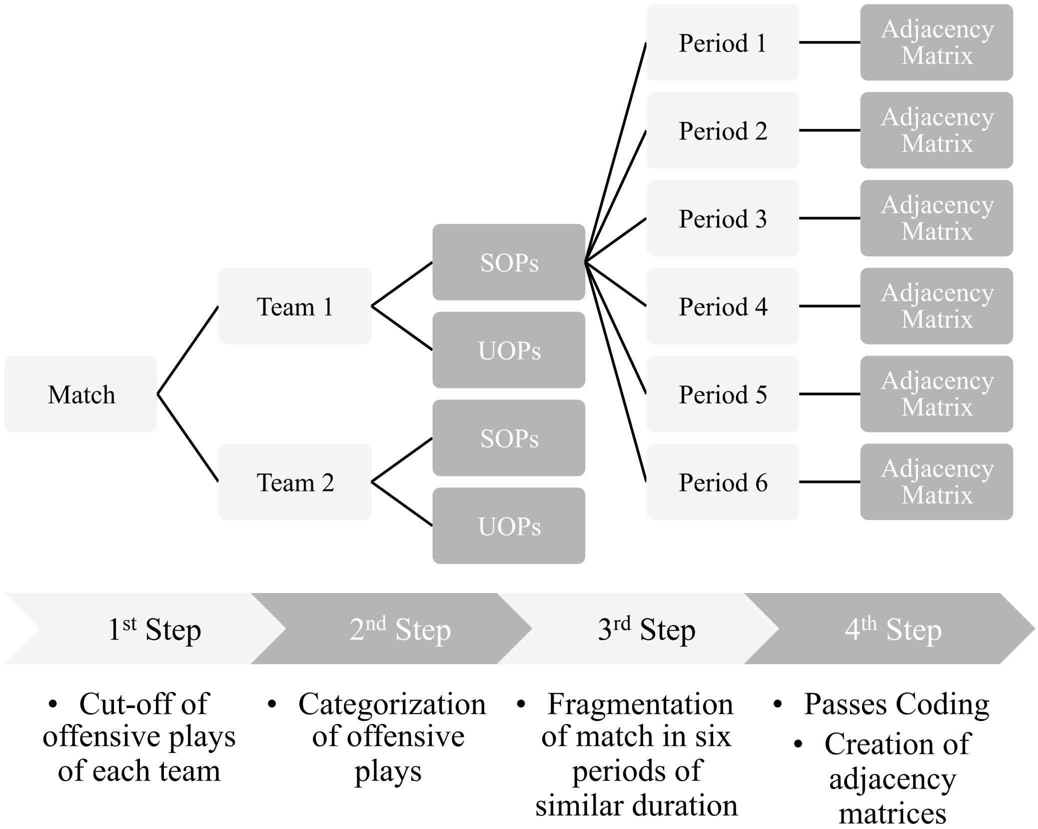


Figure 2. Process of creation of adjacency matrices.

Predictor Variables

Density

Density measures the interconnectedness of nodes (players) in a network (team), i.e. it is the ratio of existing ties (passes) between teammates relative to the possible number of such ties (Balkundi & Harrison, 2006). In ordered relations, as in the teammates interactions, the possible directed links in a digraph of n nodes are $n\ (n - 1)$. The graph's density Δ is defined as the ratio between the total registered links ($\mathcal{L}$) and the maximum number of possible connections. It is calculated as:

$$\Delta = \frac{\mathcal{L}}{n\ (n-1)}$$

Thus, density is a fraction with a minimum of 0 (no lines/arcs present) and a maximum of 1 (all lines/arcs are present) (Wasserman & Faust, 1994). Considering specifically soccer team passing networks, as analyzed in present study, values of density closer to 1 suggest a very intense relationship between teammates, with most players interacting with each other through passing. Such strong relationships increase mutual interdependence between teammates (Sparrowe, Linden, Wayne, & Kraimer, 2001), which promote cooperation and a coordination of efforts.

Clustering Coefficient

Clustering is a measure of the degree to which nodes in a network tend to cluster together (Peña & Touchette, 2012). The clustering coefficient, originally introduced by Watts & Strogatz (1998), quantifies how close a node and its neighbors in a graph are to becoming a complete subgraph.

In directed graphs, the local clustering coefficient of a vertex expresses the ratio of the links between the vertices that are connected to it. Thus, local clustering coefficient (C_i) of a given vertex i is the fraction of the number of connections a_{jk} between k_i vertices in its neighborhood, divided by the maximum number $k_i\ (k_i - 1)$ of possible links between them:

$$C_i = \frac{\left|\{a_{jk}, a_{jk} \in E\}\right|}{k_i(k_i - 1)}$$

We used a variant of the clustering coefficient - the average local clustering coefficient - to measure the clustering level throughout the network:

$$\overline{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$$

Centralization

The centrality of a group or network is the degree of inequality of the distribution of positions/ "weights" of different elements within the network. A network is therefore more centralized when one of its elements is clearly more central than all other group members. Conversely, a network is decentralized when all its elements have the same value of centrality (Grund, 2012).

There are several measures of centrality and researchers do not always agree on how "group centrality" or "centralization" should be assessed. We used degree centrality for quantifying the relative influence of each player on the total number of passes within a network. Thus, centralization conveys how central the most central player is when compared to the other players in the network. This metric was originally described by Freeman (1978) and is calculated as the sum of the differences between the vertex with the highest degree centrality and all other vertexes; divided by a value depending only on the size of the network:

$$C_D = \frac{\sum_{i=1}^{n} \deg(v^*) - \deg(v)}{n^2 - 3n + 2}$$

where deg (v^*) is the largest value of centrality degree in the network, deg (v) is the value of each vertex centrality degree, and the denominator is the maximum possible sum of differences in $i = 1$ vertex centrality for a graph of n vertexes (Freeman, 1978).

In the context of a soccer match, zero centralization indicates that all players have the same level of interaction during the game. Conversely, a centralization value very close to one suggests that a player is the key-player of the team and that other players have a strong tendency to play with him (Clemente et al., 2015a).

Analysis

A hierarchical logistic regression model was used to predict the successfulness of offensive plays from the number of passes performed and the network metrics (density, clustering coefficient and centralization). Two blocks were defined. In the first block, only the predictor *total passes* was introduced. In the second block, we introduced the network metrics. By defining *total passes* as moderator variable we could test the possible independent effect of the network metrics. Preliminarily, the data was screened for collinearity problems and outliers. Following the recommendations in Belsley et al. (1980), we diagnosed collinearity when conditioning indexes were greater than 30 for a given dimension and the variance proportions were greater than 0.5 for more than one variable. The latter was true for the pairs of variables "clustering coefficient and centralization" and "total passes and density", however, both of these dimensions registered conditioning indexes below 30 (12.224 and 22.655, respectively). Thus, it was not necessary to transform or eliminate any predictor-variable. Next, we obtained *z*-scores and searched for outliers greater than 3.29 (Tabachnick & Fidell, 2013). A single outlier was identified (z-score = 4.378) and removed. Additionally, four SOP cases were removed because they registered "no passes". After these preliminary procedures, 283 of the initial 288 cases were kept for further analysis, corresponding to 144 cases of UOP and 139 of SOP.

In a logistic regression, Exp (β_i) represents the odds-ratio of success versus failure (categories of the model's dependent variable) when variable X_i increases by one unit with respect to the odds-ratio of success versus failure, when X_i stays constant. Density, clustering coefficient and centralization vary between zero and one, therefore, we converted these metrics to a scale of zero to ten to adjust adequately model sensitivity. Consequently, the odds ratios presented for these variables refer to a unit change of 0.1.

Results

Characterizing the four potential predictors by team (see Table 1), it can be seen that the GSK and SLB teams are those that, in the four potentially predictor variables, are closer to the mean value. In a different way, we realize that both the CAM and FCA teams move away from these averages, each of which is the team that registers, for the four metrics, the highest and lowest values, respectively.

A two-block hierarchical logistic regression was used to predict the successfulness of offensive plays. In the first block, the total number of passes (hereafter referred to as 'total passes') was the only predictor-variable. This model performed significantly better than a constant-only model ($G^2_{(1,N=283)} = 7.484, p = 0.006$), but it did not satisfy goodness-of-fit criteria (Hosmer and Lemeshow test: $\chi^2_{(8,N=283)}$= 25.342 p = 0.001), and it produced a Nagelkerke r^2 of 0.035. Network metrics were added in a second block (Table 2). This

Table 1. Characterization of offensive plays' successfulness potential predictor variables.

	Overall n = 283	Team			
		CAM n = 70	FCA n = 72	GSK n = 69	SLB n = 72
Total Passes	24,12 ± 15,16	30,10 ± 15,96	17,72 ± 11,37	24,46 ± 15,91	24,39 ± 14,73
Density	0,17 ± 0,09	0,20 ± 0,09	0,14 ± 0,08	0,18 ± 0,09	0,18 ± 0,08
Clustering Coefficient	0,21 ± 0,14	0,25 ± 0,14	0,14 ± 0,12	0,21 ± 0,14	0,22 ± 0,12
Centralization	0,32 ± 0,10	0,35 ± 0,09	0,28 ± 0,10	0,32 ± 0,11	0,31 ± 0,09

Data are reported as mean ± SD.

second model performed better than a constant-only model ($G^2_{(1,N=283)} = 15.484, p = 0.004$) and satisfied goodness-of-fit criteria (Hosmer and Lemeshow test: $\chi^2_{(8,N=283)}$= 7.187; p = 0.517), achieving a Nagelkerke r^2 of 0.071. The first-block model correctly classified 56.2% of the known cases, 66.7% of the UOP cases, and 45.3% of the SOP cases. The second-block model correctly classified 69.5% of the UOP cases and 47.5% of the SOP cases, with an overall correct classification of 58.7% of the cases. Thus, adding the second block to the model increased the number of correct classifications by 2.5%.

Table 2. Binary Logistic Regression Model of offensive plays' successfulness.

	β (S.E.)	Wald	p	Exp (β)	Exp (β) 95% C.I	
					Lower	Upper
Total Passes	0.079 (0.034)	5.475	0.019	1.082	1.013	1.156
Density	-1.320 (0.591)	4.994	0.025	0.267	0.084	0.850
Clustering Coefficient	0.179 (0.193)	0.858	0.354	1.196	0.819	1.747
Centralization	0.189 (0.143)	1.759	0.185	1.208	0.914	1.597
Constant	-0.615 (0.469)	1.719	0.190	0.541		

Successful Offensive Play (SOP) is the reference category of successfulness predicted in the model.

Classification was unimpressive, with 69,5% of the UOP (specificity) and 47,5% of the SOP correctly predicted (sensibility), for an overall success rate of 58,7%. We tested the model's discriminant power (between UOP and SOP) with a ROC curve (see Figure 3), and its classification capacity was confirmed (ROC c = 0,609; p = 0,002; 95% CI [0.544, 0675]).

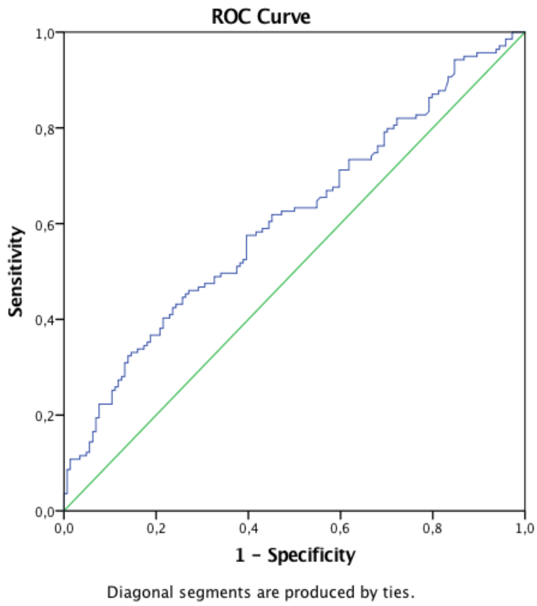


Figure 3. ROC curve of regression model of offensive play's successfulness.

Total number of passes and density were the significant predictors among the four considered variables. The total number of passes was positively associated with the successfulness of offensive plays. A one-pass-increase augmented the probability of successful offensive plays by 8.2% (Exp (β) = 1.082; see Table 2). More significantly, a 10% decrease in density increased the chances for a successful offensive play by 73.3% (Exp (β) = 0.267; see Table 2).

Results for overall data show that offensive plays with density values between 0 and 0.25 are mostly UOPs (see Figure 4). It is also noted that the majority of offensive plays expressed densities between 0.1 and 0.25. For values higher than 0.25 the cases are mostly SOPs, having also been observed an increasing mean predicted probability of SOP occurrence (see Figure 5). Otherwise, if we consider the clustering coefficient, it was verified that UOPs are characterized by clustering coefficients between 0 and 0.3, while SOPs most frequently expressed clustering coefficients between 0.2 and 0.45. The mean

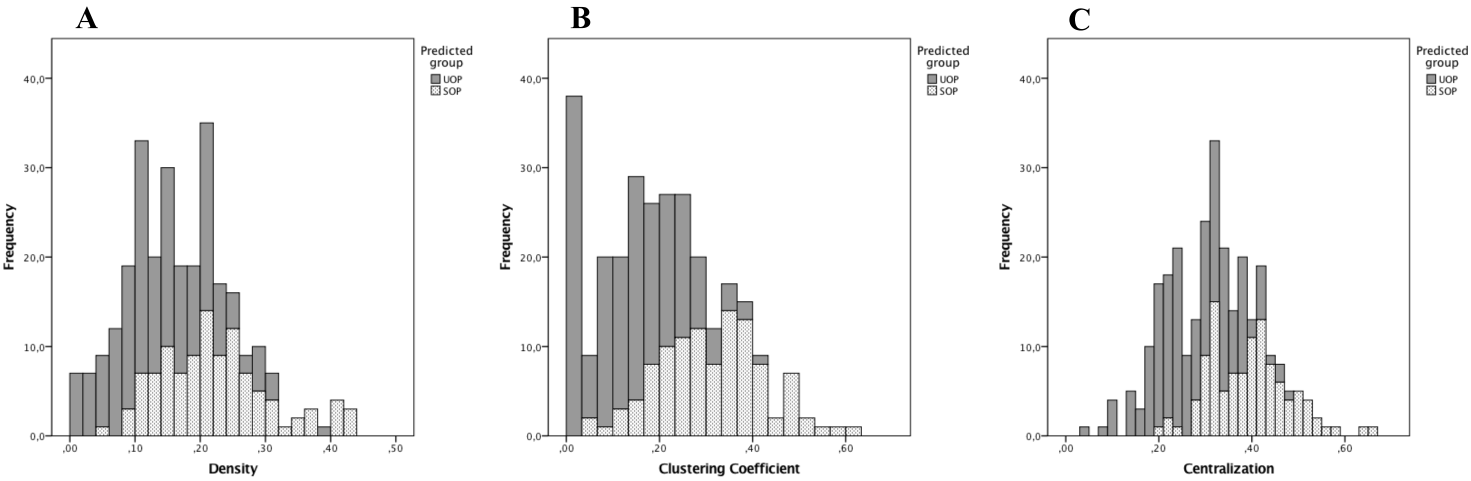


Figure 4. Frequencies of SOP and UOP cases according to: density (A), clustering coefficient (B) and centralization values (C).

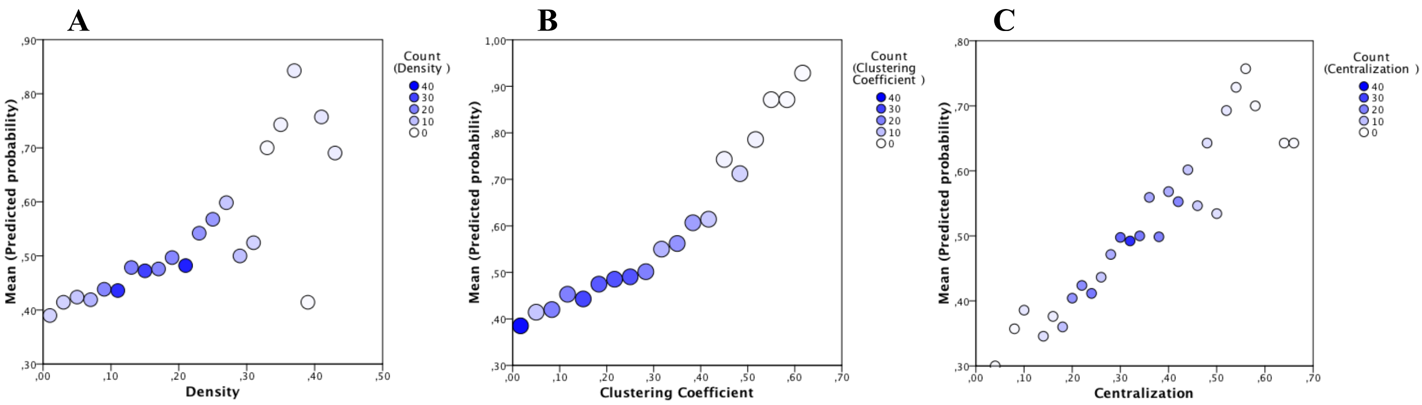


Figure 5. Relation between values of mean predicted probability and density (A), clustering coefficient (B) and centralization values (C), colored by frequencies.

predicted probability of SOPs occurrence grows as offensive plays expressed higher clustering coefficients. Furthermore, it was observed that the centralization of UOPs varied between 0 and 0.45, with greater frequencies for values between 0.2 and 0.4. On the other hand, SOPs conveyed centralizations between 0.2 and 0.65, but mostly between 0.3 and 0.45. As verified for the other metrics, SOPs mean predicted probability accompanied the increasing centralization.

When we look at the results of the model team-by-team we found that the associations observed for the general data remained with respect to clustering coefficient coefficients and centralization. The same was not true in the case of density, since the SLB team presented a more erratic relationship, having registered for values of density higher than

0.25, some cases with mean predicted probability of SOPs occurrence either high or low (see Figure 6).

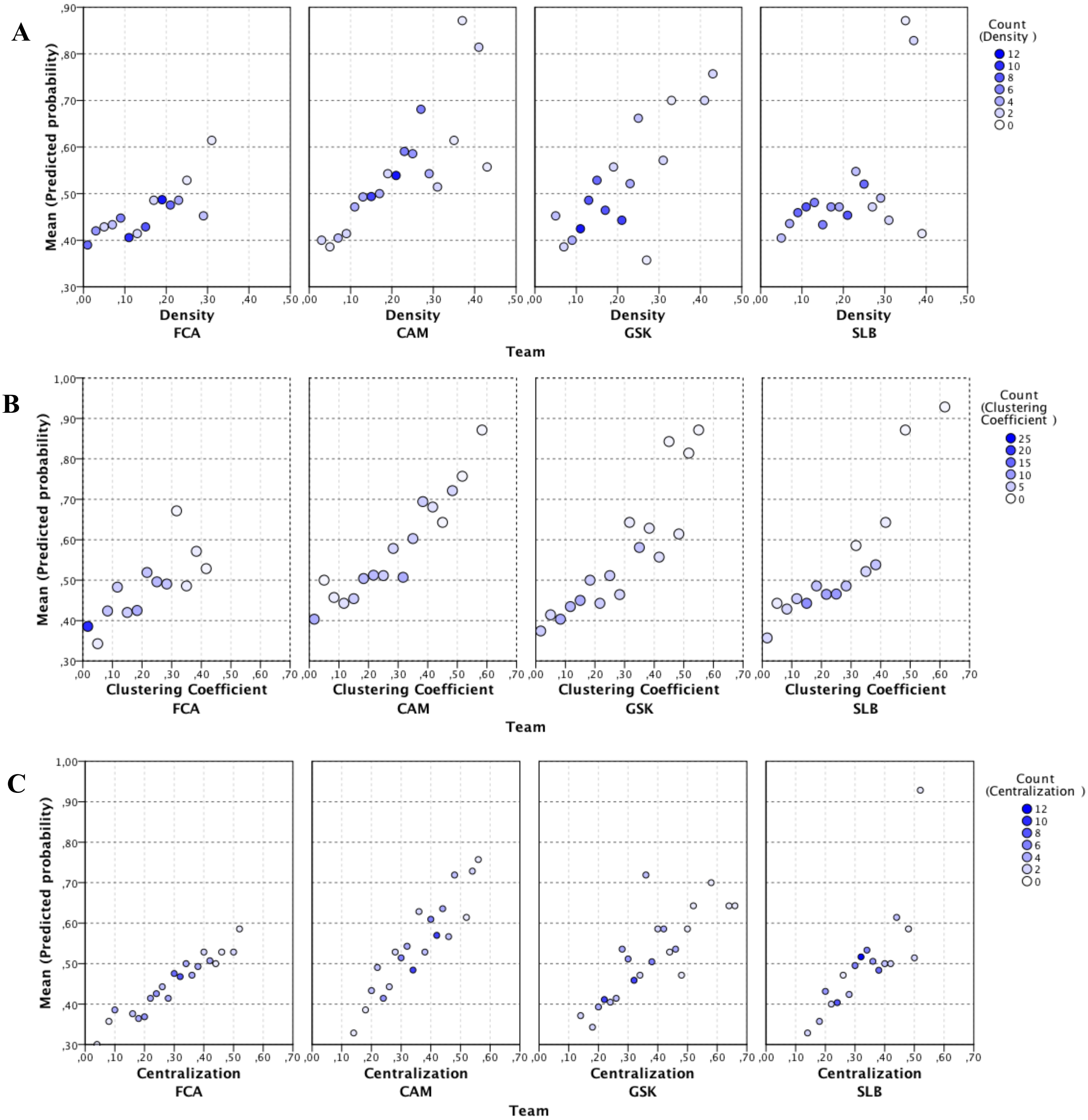
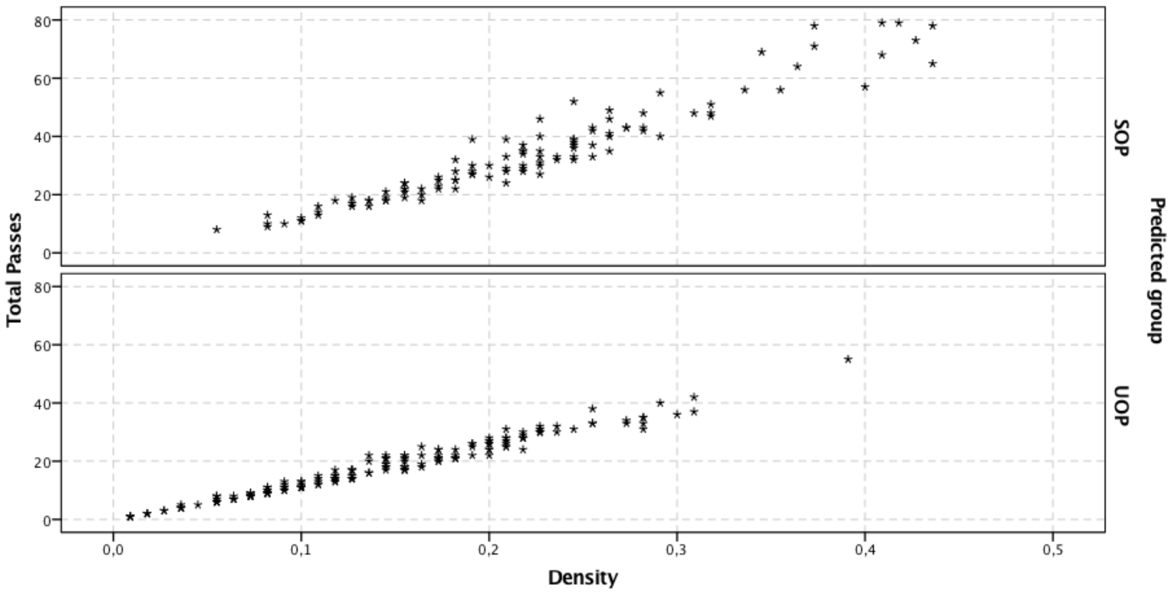


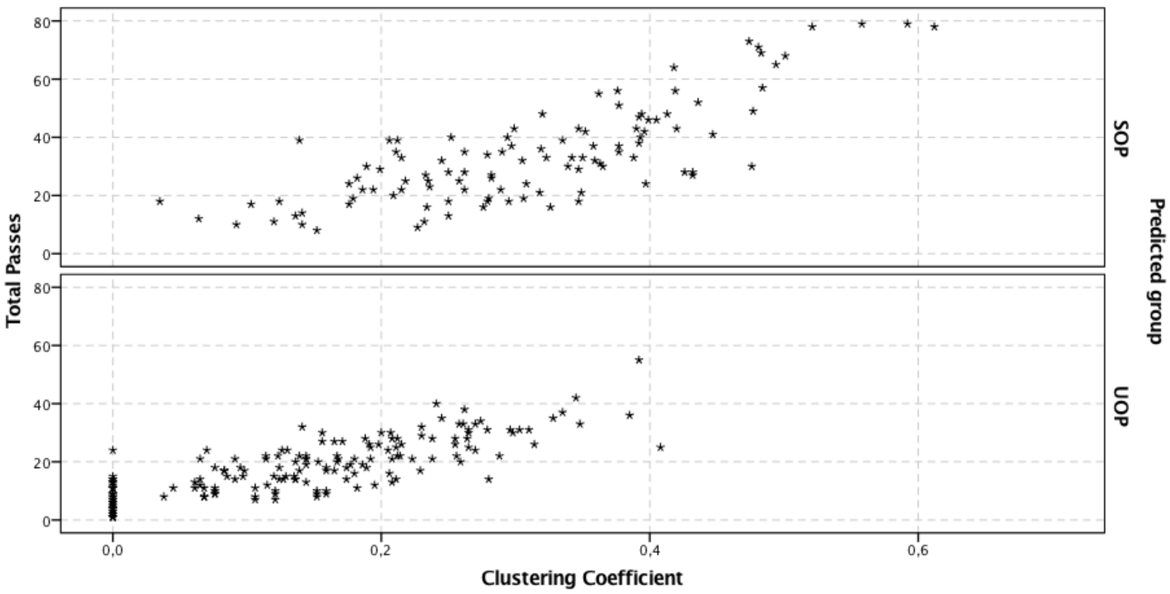
Figure 6. Team-by-team relation between values of mean predicted probability and density (A), clustering coefficient (B) and centralization values (C), colored by frequencies.

Regarding the relationship between the moderator variable, total passes, and the network metrics, there were some differences between SOPs and UOPs, considering all network metrics (see Figure 7). For density the relation seems similar until the value of 0.25 - as the density increases the number of passes also increases. While this is true also for values greater than 0.25, it’s important to note that offensive plays which combined high densities with high pass numbers were mostly SOPs. In addition, UOPs were characterized by having concomitantly expressed values of clustering coefficient and of total number of passes lower than SOPs, not having, for example, been verified any UOP with clustering coefficient equal or superior to 0.5 or a total number of passes equal to or greater than 60. This tendency for lower combinations between total number of passes and clustering coefficient seems to be maintained in case of centralization, with a great frequency of

A



B



C

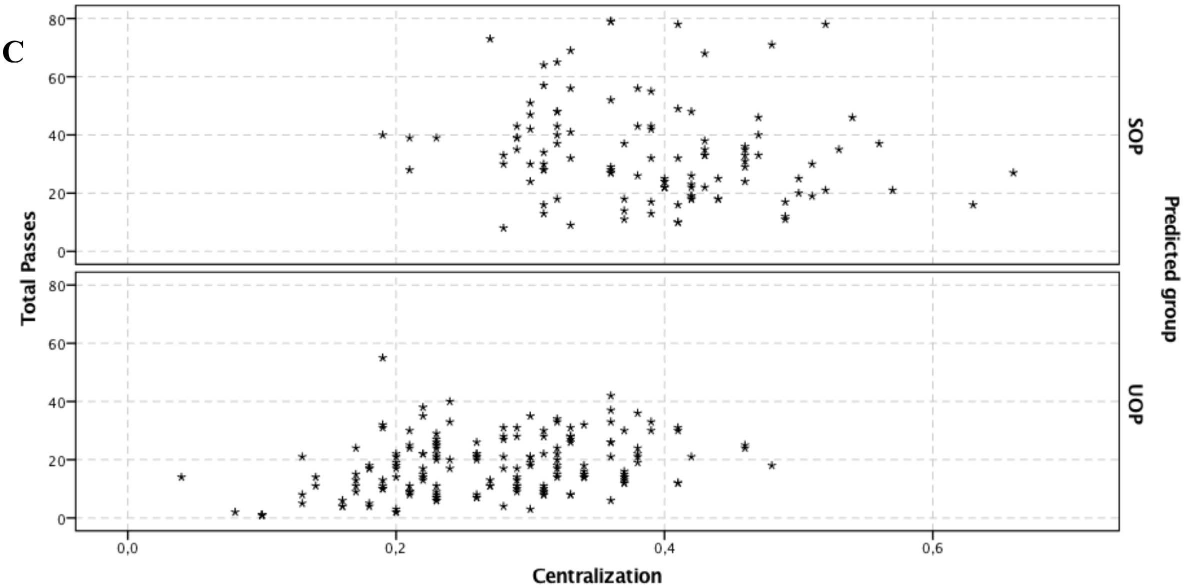


Figure 7. Relation between total passes values and density (A), clustering coefficient (B) and centralization values (C) for SOP and UOP cases. (see previous page).

UOPs for centralizations between 0 and 0.3 combined with total numbers of passes between 0 and 40. Otherwise SOPs registered higher centralizations (between 0.2 and 0.6) combined with also higher number of total passes (between 0 and 80).

Discussion

Network characteristics such as density, clustering coefficient and centralization have been reported as good descriptors of game style in soccer teams, as they can be associated with metrics of success such as goals scored, shots, shots on goal, and competition stage reached by teams. However, since network analysis describes events occurring during entire matches, performance outputs and network properties metrics cannot be measured simultaneously. In this study, we attempted to clarify the association between specific network properties and successful (or unsuccessful) team behavior.

Our model was able to classify 58.7% of the events correctly, however, it performed better at identifying UOPs (69.5%) than SOPs (47.5%). These results suggest that these network metrics (density, clustering coefficient and centralization) can more accurately describe the team behaviors associated with UOPs (i.e. losing ball possession) than the behaviors leading to SOPs (i.e. moving into the finishing zone or shooting on goal). Thus, the model can accurately pinpoint the collective behaviors that the teams should avoid in order to ensure success.

The total number of passes and density were the most relevant variables in our model. Total passes was introduced in the study as a moderator variable to assess the independent influence of the network metrics on team performance. The improvement in the model obtained by adding the second block confirmed the metrics' independent influence. We observed a positive association between total passes and team performance. Each pass increment in a set of offensive plays occurring within a 15 minute-period resulted in the teams being 8.2 % more likely to move into the finishing zone or to shoot on goal. The density of a ball-passing network increases whenever two players who were not yet connected pass the ball between them; in this way, high density is probably associated to high occurrence of these differentiated links. This greater variability of pass patterns, which is expressed in qualitatively distinct connections over a given period, may occur for different reasons. For example, greater collective dynamics and high player mobility can result in passes between players who regularly play in distant areas.

It has been shown that strong cooperation between teammates makes teams stronger and more successful (Balkundi & Harrison, 2006). Thus, how can we explain our results showing that density has a negative effect (albeit small) on the successfulness of offensive plays? As can be seen in Figure 1, for density values ranging from 0 to 0.25 our model predicts mostly UOP outcomes. When we consider only events classified as SOP, there is a high number of offensive plays with density values ranging from 0.1 to 0.25, followed by a decrease. This drop in the number of offensive plays for higher density values could explain the negative association between density and SOPs. Indeed, despite being associated with fewer SOPs overall, higher densities are more likely to lead to SOPs (see Figure 2). Thus, our results suggest that density values lower than 0.25 are associated with a higher number of offensive plays, albeit mostly unsuccessful ones. Conversely, for density values above 0.25 there may be fewer offensive plays overall but most are successful. It is unlikely though that this negative association between density and SOPs is simply due to the higher number of errors and losses that result from the players' greater efforts to maintain connections in high-density scenarios (Burt, 1997). Instead, it seems more plausible that the reduction in SOP outcomes observed for density values above 0.25 explains that negative association. Indeed, these offensive plays with high-density values are characterized by a higher number of passes (see Figure 2), which could explain why there are fewer (but more successful) offensive plays in the same period of time. For example, these high-density values may result from longer ball-possession times, fewer ball possession losses, or specific losses in advanced zones of the field (finishing zone). This hypothesis is consistent with our observation that qualitatively differentiated links are associated with high densities, which likely reflects a greater unpredictability of passing patterns. Furthermore, it was previously proposed that greater variability of action and less exposure to the opponent could result from decentralized passing patterns (Gréhaigne et al., 1997). Such characteristics of offensive plays associated with high-density values contribute to an offensive process that creates goal-scoring opportunities and are more effective for maintaining ball possession in advanced areas. Interestingly, offensive plays with similar characteristics have been observed in successful teams at the FIFA World Cup 2014 (Clemente et al., 2015c).

When we analyse the results team by team, we confirm what several authors have already stated: teams that reach more advanced stages of competitions have higher average values of density (Clemente et al., 2015c). Thus CAM team, the first classified in the group and finalist of the competition, had the highest mean density (0,20 ± 0.09) and FCA team, fourth in the group, had the lowest value (0,14 ± 0.08).

As for the association between density values and the success of offensive plays (see Figure 6), we found that for CAM and GSK teams, the relation between density and success is similar to what was previously exposed to the overall values of all teams. Still, for CAM team the failure is more unlikely to occur at values of density lower than those verified for all of the other teams, since from the density value of 0.2 CAM team does not register any set of offensive plays with mean predicted probability less than 0.5. It is curious to note, however, that the same trend does not occur for all teams. As far as FCA team is concerned, the fact that it did not register densities above 0.3 makes it impossible to draw conclusions about the measure of the success of supposed offensive plays that would reflect these density values. Nevertheless, the set of offensive plays that registered the highest mean predicted probability was the only one located above densities of 0.3, which may be indicative. What was more curious was to verify that for SLB team it was difficult to establish any association between any values of density and the offensive plays' successfulness. Although some sets of offensive plays with densities between 0.35 and 0.40 expressed a fairly high predicted probability of being SOP, the trend for the remaining observations is even slightly negative. This last observation may help to explain, along with the previous described, the odd-ratio that expresses the negative association between the global values of density and the success of offensive plays, and seems to suggest that relation between density and successful performance isn't independent of team effect.

We found that the clustering coefficient is not a significant predictor of the successfulness of offensive plays, thus corroborating previous research (Gudmundsson & Horton, 2016; Peña & Touchette, 2012). However, our model indicates that a 10% increase in the clustering coefficient augments by 19.6% the probability of an SOP outcome (see also Clemente et al., 2015c). Furthermore, the association between high values of number of passes and clustering coefficient (see Figure 7) is in line with findings of Yamamoto (2009). High clustering coefficient values express the subgroup formation within the team itself; when these subgroups are created based on passes between teammates, as in the present study, the players performing in close areas tend to be linked together, thereby explaining the high clustering coefficients. This could reflect an offensive style choice based on short combinations between players, as previously observed for the Spain, Germany and Netherlands national teams at the FIFA World Cup 2010 (Cotta, Mora, Merelo-Molina, & Merelo, 2011; Peña & Touchette, 2012). Thus, the modest contribution of the clustering coefficient to the predictive value of our model suggests that different offensive styles may lead to successful team performance, depending, for example, on the players' individual qualities or on different strategic options. Further investigation is needed to clarify this issue.

Our results demonstrate that centralization is not consistently associated with successfulness of offensive plays, which is in agreement with findings by Fewell, Armbruster, Ingraham, Petersen, and Waters (2012) showing that there is no strong relationship between centralization and team performance. However, we found a positive effect of centralization on successful team performance, as a 10% increase in centralization increases by 20.8 % the chances of an SOP. This result contradicts a previous report showing that higher centralization is associated with worse team performance (goals scored) (Grund, 2012). This discrepancy could, however, be explained by the different methodologies in these studies, as discriminating successful and unsuccessful performances probably influenced the relationship between centralization and successful team performance in our study.

In summary, our results suggest that network density can accurately predict the ability of a team to enter the finishing zone or to shot on goal in elite soccer. Furthermore, this study gives new insights into the association between network density and team performance (Balkundi & Harrison, 2006). First, we showed that low network density may be associated with a higher overall number of offensive plays but which were mostly unsuccessful. Second, high density was associated with fewer and/or longer offensive plays, which reduces the possibilities of a team moving into the finishing zone (hence decreasing total SOPs), thus resulting in a negative association between density and SOPs. Finally, we considered that high density may also be associated with fewer ball-possession losses before the teams reach the finishing zone (hence increasing probability of SOPs), thereby supporting the density-performance hypothesis. Analyzing team-by-team it was found that relation between team performance and density seems to depend on style of play.

Some practical implications can be inferred from the present findings. Success of teams that express high densities in their offensive processes is eventually dependent on the creation of numerous lines of pass to the player with the ball. In light with ecological dynamics (Araújo, Davids, & Hristovski, 2006), this might be enhanced in the training sessions by manipulating task constraints, such as: i) using different relationships among depth / width of the field, to facilitate a team entering the finishing zone using different space channels; (ii) performing ball possession games with numerous mini-goals dispersed in the field, so that the player with the ball searches for 360° lines of pass; iii) performing games with varied ratios between the number of players and the area, to induce variability in the distance of the lines of pass and the type of passes required. On the other hand, for teams that express a lower density, some task constraints may be: i) establishment of a time limit for the performance of offensive plays, in order to enhance the entries in the finishing zones with fewer connections; ii) performing small-sided games with few players (1x1, 2x2, 3x3) to promote brief attacking actions with stable connections; iii) improving relationships between specific players, according to preferential links, by placing such players in the same team in small-sided games or in the training of specific collective actions among them.

We tested a model that analyzed the specific associations between the characteristics of a team's ball-passing network and the outcome of its offensive plays (entering the finishing zone and shot on goal vs losing ball possession). Previous studies had not differentiated these different outcomes, which may explain our results revealing a negative relation between density and team performance. Finally, we demonstrated that neither clustering coefficient nor centralization significantly contribute to the prediction of team performance successfulness, possibly indicating that diverse offensive styles can be equally effective for a team to succeed.

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Appendix I

Network characteristics of successful performance in team sports. A study on the UEFA Champions League

frontiers

Network characteristics of successful performance in team sports. A study on the UEFA Champions League

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Abstract

The synergistic interaction between teammates in association football has properties that can be captured by Social Network Analysis (SNA). The analysis of networks formed by team players passing a ball in a match shows that team success is correlated with high network density and clustering coefficient, as well as with reduced network centralization. However, oversimplification needs to be avoided, as network metrics events associated with success should not be considered equally to those that are not. In the present study, we investigated whether network density, clustering coefficient and centralization can predict successful or unsuccessful team performance. We analyzed 12 games of the Group Stage of UEFA Champions League 2015/2016 Group C by using public records from TV broadcasts. Notational analyses were performed to categorize attacking sequences as successful or unsuccessful, and to collect data on the ball-passing networks. The network metrics were then computed. A hierarchical logistic-regression model was used to predict the successfulness of the offensive plays from network density, clustering coefficient and centralization, by using total passes as a moderator variable. Results confirmed the independent effect of network metrics. Density, but not clustering coefficient or centralization, was a significant predictor of the successfulness of offensive plays. We found a negative relation between density and successfulness of offensive plays. However, reduced density was associated with a higher number of offensive plays, albeit mostly unsuccessful. Conversely, high density was associated with a lower number of successful offensive plays, but also with overall fewer offensive plays and "ball possession losses" before the attacking team entered the finishing zone. Independent SNA of team performance is important to minimize the limitations of oversimplifying effective team synergies.

1 Introduction

The team, rather than the individual, has become the basic work unit in many activities and organizations (Balkundi & Harrison, Ties, leaders, and time in teams: strong inference about network structure's effects on team viability and performance., 2006), and team sports are excellent examples revealing the importance of team dynamics for success (Duch, Waitzman, & Amaral, 2010). A team is a group of individuals working cooperatively and in a coordinated way to achieve a common goal (Zaccaroa, Rittmana, & Marks, 2001). Team performance is more than the sum of the interdependent individual performances, as individuals strive to coordinate between different roles and tasks (Anderson & Franks, 2001). In team sports performance, individual players in a successful team act as a coherent unit, thus creating a team synergy (Araújo & Davids, 2016).

Individual and collective behavior has been intensively studied in team sports performance analysis. The behavior of an individual player affects the team's behavioral pattern (Vilar, Araújo, Davids, & Button, 2012), and conversely, the teammates may influence the behavior of each individual player. Team behavior is a collective organization that emerges from the cooperation between teammates (Gréhaigne, Bouthier, & David, 1997; Peña & Touchette, 2012). The emergence of such collective behaviors can be assessed and understood through the measurement of key synergistic properties such as degeneracy, i.e., the structurally different components that perform a similar (but not necessarily identical) function in a given context (Araújo & Davids, 2016). The degeneracy of team behavior as a social relationship property can be captured by Social Network Analysis (SNA) (Grund, 2012; Peña & Touchette, 2012). SNA has been applied to association football or soccer (Clemente F. M., Martins, Couceiro, Mendes, & Figueiredo, 2014), in particular to analyze ball-passing networks in a team. These studies demonstrated that some metrics are useful to characterize styles of play and cooperation among teammates (Cotta, Mora, Merelo-Molina, & Merelo, 2011), as well as the relation between individual actions and team tactical behavior (Passos, Davids, Araújo, Paz, Minguéns, & Mendes, 2011). Centrality metrics have been used to identify the most influential tactical positions within a team. For example, by analyzing the in-degree and out-degree centrality of the Portugal national football team players, Mendes et al. (2015) found that during the FIFA World Cup 2014 the central midfielders were the key players in the attacking-building process. A similar study examining degree centrality and degree prestige of Switzerland national team players during the same competition showed that the key players receiving the ball were also the midfielders, suggesting this team has a style of play based on attacking building (Clemente F. M., Martins, Kalamaras, Oliveira, Oliveira, & Mendes, 2015). Thus, network metrics such as density, heterogeneity and centralization are effective for characterizing the cooperation between players (Clemente F. M., Couceiro, Martins, & Mendes, 2015).

Analyses of network heterogeneity and centrality reveal that team offensive play has many variations and short patterns that increase collective unpredictability (Clemente F. M., Martins, Couceiro, Mendes, & Figueiredo, 2014). Furthermore, high total links and high density can convey the team's greater ability to pass the ball between all players and to function as a whole, as well as to decentralize the network (Clemente, Martins, & Mendes, 2014). For example, a study analyzing team ball-passing networks in 760 matches of the English Premier League (Grund, (2012) showed that high levels of network intensity were associated with increased team performance (goals scored), and centralized interaction patterns with decreased team performance. More recently, similar research analyzing ball-passing networks of teams competing at the FIFA World Cup 2014 (Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015) revealed significant differences in density, total links and clustering coefficient between teams reaching different stages of the competition. These findings further demonstrate an association between higher density, total links and clustering coefficient with performance variables such as goals scored, overall shots, and shots on goal (Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015).

Despite these recent advances, research in the field has remained focused on the association between ball-passing network metrics and coarse-grained team performance variables (e.g. goals scored, shots, shots on goal, or competition stage reached) (Grund, 2012; Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015), which implies that team performance outputs and network properties metrics are measured simultaneously (Grund, 2012). However, since ball-passing network analysis offers an overall picture of events occurring during a certain period of time, typically a synthesis of several complete matches, the events leading to successful or unsuccessful team performance are included in the same analyses. Thus, it remains unknown whether specific network properties and successful (or unsuccessful) team behavior are associated. Furthermore, although previous research based on ball-passing networks suggests that high density (Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015) and low centralization (Grund, 2012) are associated with successful teams, the relation between clustering coefficients and team performance is more uncertain (Peña & Touchette, 2012; Gudmundsson & Horton, 2016). Thus, the aim of this study was to test whether team network density, centralization and clustering coefficient can be used to predict the outcome of offensive plays.

2 Materials and Methods

2.1 Sample

This study deliberately focused on club-teams rather than on national teams because club-teams train and compete together for longer consecutive periods of time. Our sample comprises 12 matches played in Group C of the UEFA Champions League 2015/2016 Group Stage. The four teams analyzed are here identified as CAM, FCA, GSK and SLB.

2.2 Procedures

Our analysis focused on collective offensive processes. Offensive play is a set of attacking actions performed by a team between recovering and losing ball possession. We considered that a team is in possession of the ball when it performs a positive pass, i.e., it maintains ball possession after the pass.

The video footage used in the analysis was obtained from TV broadcasters. We started by categorizing all offensive plays as *successful* when the attacking team entered the *finishing zone*, which was previously reported as a proxy variable for scored goals when measuring successfulness in football (Tenga, Ronglan, & Bahr , 2010). The concept of finishing zone was based on Gréhaigne et al's longitudinal division of the football field into four equal areas (Gréhaigne, Mahut, & Fernandez, 2001). These areas are designated according to the direction of the attack as follows: defensive zone, pre-defensive zone, pre-offensive zone and offensive zone. The offensive zone in elite soccer was defined as the finishing zone (Lago, Lago, Rey, Casáis, & Domínguez, 2012).

Successful offensive plays (SOPs) include plays that finished with a shot at the goal and those where the team retained ball possession until entering the finishing zone. *Unsuccessful offensive plays* (UOPs) were all the plays where the team lost ball possession without meeting either of the SOP criteria. *Neutral plays* were offensive plays where a team did not lose ball possession but also did not meet the SOP criteria. This neutral category included all offensive plays that were initiated: (i) from an offensive corner kick; (ii) in an offensive throw-in; and (iii) from offensive free kicks with a first pass directly into the finishing zone. The neutral offensive plays were not included in the present analysis.

The offensive plays were identified and categorized with *Longomatch* software from every pass performed in the 12 matches. The players who passed and received the ball were registered for each offensive play. A number from one to 11 was assigned to each player according to his initial position within the team's tactical system. The same number was assigned to players performing the same tactical position. Taking into account their different stoppage times, each half of the match was divided into three fractions with the same duration. Next, two adjacent matrixes of offensive plays (successful and unsuccessful) for each opposing team were created for the six periods of the match, in a total of 24 adjacent matrixes per match. Each of these adjacent matrixes was then imported to the software *NodeXL* to compute the networks and their metrics. All statistical procedures were performed using *SPSS Statistics 24*.

2.3 Predictor Variables

2.3.1 Density

Density is the interconnectedness of nodes (players) in a network (team), i.e. it is the ratio of existing ties (passes) between teammates relative to the possible number of such ties (Balkundi & Harrison, Ties, leaders, and time in teams: strong inference about network structure's effects on team viability and performance., 2006). In ordered relations, as in the teammates interactions, the possible directed links in a digraph of n nodes are $n\ (n-1)$. The graph's density Δ is defined as the ratio between the total registered links ($\mathcal{L}$) and the maximum number of possible connections. It is calculated as:

$$\Delta = \frac{\mathcal{L}}{n\ (n-1)}$$

Thus, density is a fraction with a minimum of 0 (no lines/arcs present) and a maximum of 1 (all lines/arcs are present) (Wasserman & Faust, 1994).

2.3.2 Clustering Coefficient

Clustering is a measure of the degree to which nodes in a network tend to cluster together (Peña & Touchette, 2012). The clustering coefficient, originally introduced by Watts & Strogatz (1998), quantifies how close a node and its neighbors in a graph are to becoming a complete subgraph.

In directed graphs, the local clustering coefficient of a vertex expresses the ratio of the links between the vertices that are connected to it. Thus, local clustering coefficient (C) of a given vertex i is the fraction of the number of connections a_{jk} between k_i vertices in its neighborhood, divided by the maximum number $k_i\ (k_i - 1)$ of possible links there between:

$$C_i = \frac{\left|\{a_{jk}, a_{jk} \in E\}\right|}{k_i(k_i - 1)}$$

We used a variant of the clustering coefficient - the average local clustering coefficient - to measure the clustering level throughout the network:

$$\overline{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$$

2.3.3 Centralization

The centrality of a group or network is the degree of inequality of the distribution of positions/ "weights" of different elements within the network. A network is therefore more centralized when one of its elements is clearly more central than all other group members. Conversely, a network is decentralized when all its elements have the same value of centrality (Grund, 2012).

There are several measures of centrality and researchers do not always agree on how "group centrality" or "centralization" should be assessed. We used degree centrality for quantifying the relative influence of each player on the total number of passes within a network. Thus, centralization conveys how central the most central player is when compared to the other players in the network. This metric was originally described by Freeman (1978) and is calculated as the sum of the differences between the vertex with the highest degree centrality and all other vertexes; divided by a value depending only on the size of the network:

$$C_D = \frac{\sum_{i=1}^{n} \deg(v^*) - \deg(v)}{n^2 - 3n + 2}$$

where deg (v^*) is the largest value of centrality degree in the network, deg (v) is the value of each vertex centrality degree, and the denominator is the maximum possible sum of differences in $i = 1$ vertex centrality for a graph of n vertexes (Freeman, 1978).

In the context of a football match, zero centralization indicates that all players have the same level of interaction during the game. Conversely, a centralization value very close to one suggests that a player is the key-player of the team and that other players have a strong tendency to play with him (Clemente F. M., Couceiro, Martins, & Mendes, 2015).

2.4 Analysis

A hierarchical logistic regression model was used to predict the successfulness of offensive plays from the number of passes performed and the network metrics (density, clustering coefficient and centralization). Two blocks were defined. In the first block, only the predictor *total passes* was introduced. In the second block, we introduced the network metrics. By defining *total passes* as moderator variable we could test the specific influence of the network metrics. Preliminarily, the data was screened for collinearity problems and outliers. Following the recommendations in Belsley et al. (1980), we diagnosed collinearity when conditioning indexes were greater than 30 for a given dimension and the variance proportions were greater than 0.5 for more than one variable. The latter was true for the pairs of variables “clustering coefficient and centralization” and “total passes and density”, however, both of these dimensions registered conditioning indexes below 30 (12.224 and 22.655, respectively). Thus, it was not necessary to transform or eliminate any predictor-variable. Next, we obtained *z*-scores and searched for outliers greater than 3.29 (Tabachnick & Fidell, 2013). A single outlier was identified (z-score = 4.378) and removed. Additionally, four SOP cases were removed because they registered “no passes”. After these preliminary procedures, 283 of the initial 288 cases were kept for further analysis, corresponding to 144 cases of UOP and 139 of SOP.

In a logistic regression, Exp (β_i) represents the odds-ratio of success versus failure (categories of the model’s dependent variable) when variable X_i increases by one unit with respect to the odds-ratio of success versus failure, when X_i stays constant. Density, clustering coefficient and centralization vary between zero and one, therefore, we converted these metrics to a scale of zero to ten to adjust to model sensitivity. Consequently, the odds ratios presented for these variables refer to a unit change of 0.1.

3 Results

A two-block hierarchical logistic regression was used to predict the successfulness of offensive plays. In the first block, the total number of passes (hereafter referred to as 'total passes') was the only predictor-variable. This model performed significantly better than a constant-only model ($G^2_{(1,N=283)} = 7.484, p = 0.006$), it did not satisfy goodness-of-fit criteria (Hosmer and Lemeshow test: $\chi^2_{(8,N=283)}$= 25.342 p = 0.001), and it produced a Nagelkerke r^2 of 0.035. Network metrics were added in a second block (Table 1). This second model performed better than a constant-only model ($G^2_{(1,N=283)} = 15.484, p = 0.004$) and satisfied goodness-of-fit criteria (Hosmer and Lewenshow test: $\chi^2_{(8,N=283)}$= 7.187; p = 0.517), achieving a Nagelkerke r^2 of 0.071. The first-block model correctly classified 56.2% of the known cases, 66.7% of the UOPs and 45.3% of the SOPs. The second-block model correctly classified 69.5% of the UOPs and 47.5% of the SOPs, with an overall correct classification of 58.7% of the cases. Thus, adding the second block to the model increased the number of correct classifications by 2.5%.

TABLE 1 | Binary Logistic Regression Model of offensive plays' successfulness.

	β (S.E.)	Wald	p	Exp (β)	Exp (β) 95% C.I	
					Lower	Upper
Total Number of Passes	0.079 (0.034)	5.475	0.019	1.082	1.013	1.156
Density scores	-1.320 (0.591)	4.994	0.025	0.267	0.084	0.850
Clustering Coefficient scores	0.179 (0.193)	0.858	0.354	1.196	0.819	1.747
Centralization scores	0.189 (0.143)	1.759	0.185	1.208	0.914	1.597
Constant	-0.615 (0.469)	1.719	0.190	0.541		

Successful Offensive Play (SOP) is the reference category of successfulness predicted in the model.

Total number of passes and density were significant predictors among the four considered variables. The total number of passes was positively associated with the successfulness of offensive plays. A one-pass-increase augmented the probability of successful offensive plays by 8.2% (Exp (β) = 1.082; see Table 1). More significantly, a 10% decrease in density increased the chances for a successful offensive play by 73.3% (Exp (β) = 0.267; see Table 1). Furthermore, for density values ranging from 0 to 0.25 there is a similar relation between total passes and number of either SOPs or UOPs (see Figure 2), despite the higher frequency of UOPs (see Figure 1). However, for density values above 0.25, as the number of total passes increases, we see a tendency for a decrease in both SOPs and UOPs, but a predominant occurrence of SOPs in relation to UOPs.

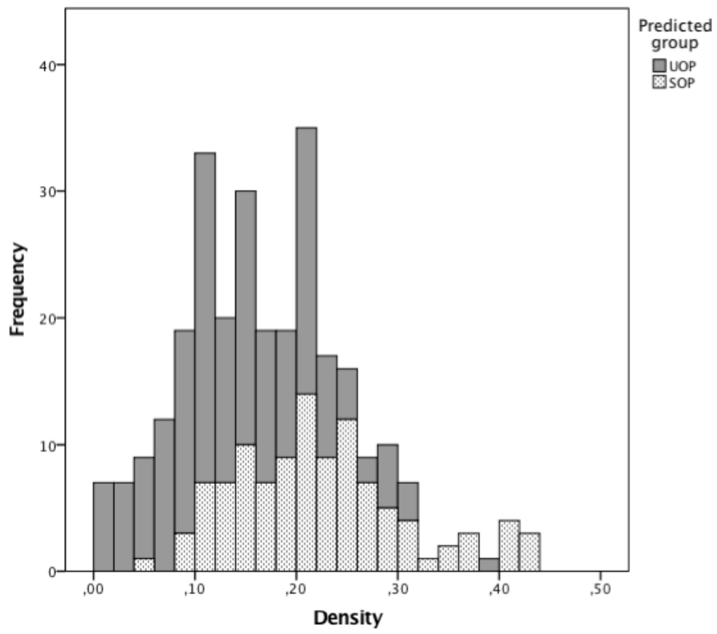

FIGURE 1 - Frequencies of density values, according to the category of offensive play's successfulness.

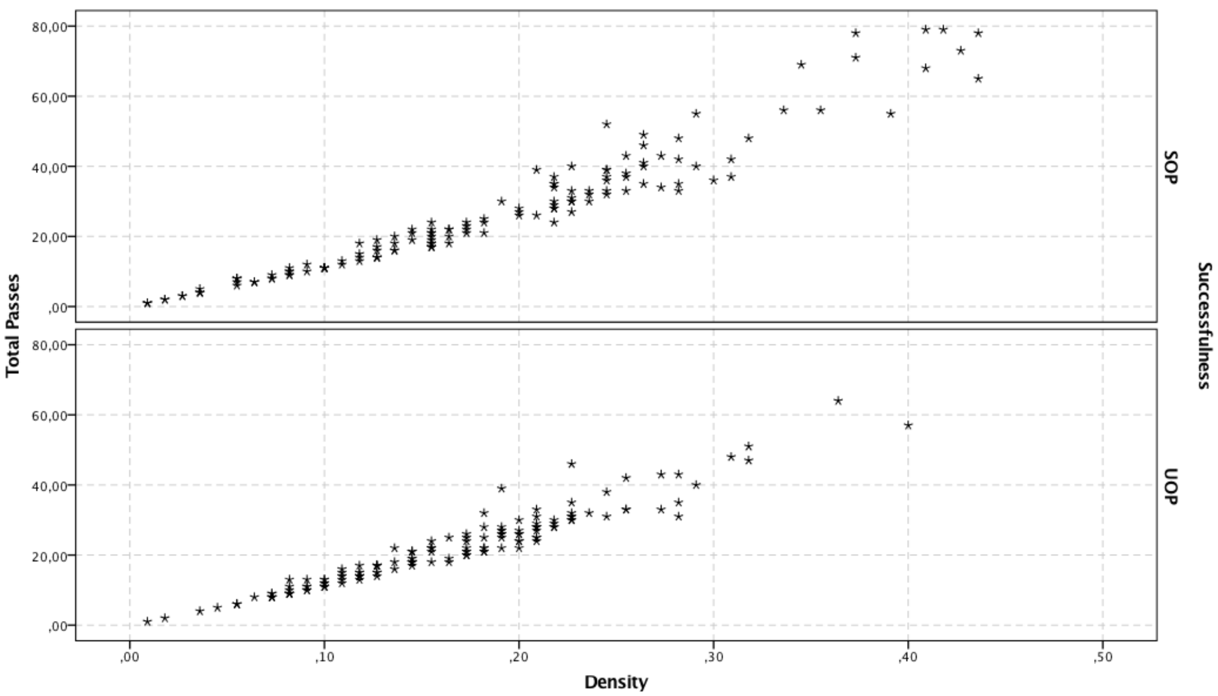

FIGURE 2 - Relationship between density and total passes, for SOP and UOP outcomes, according to the second-block logistic regression model.

4 Discussion

Network characteristics such as density, clustering coefficient and centralization have been reported as good descriptors of game style in soccer teams, as they can be associated with metrics of success such as goals scored, shots, shots on goal, and competition stage reached by teams. However, since network analysis describes events occurring during entire matches, performance outputs and network properties metrics cannot be measured simultaneously. In this study, we attempted to clarify the association between specific network properties and successful (or unsuccessful) team behavior.

Our model was able to classify 58.7% of the events correctly, however, it performed better at identifying UOPs (69.5%) than SOPs (47.5%). These results suggest that these network metrics (density, clustering coefficient and centralization) can more accurately describe the team behaviors associated with UOPs (i.e. losing ball possession) than the behaviors leading to SOPs (i.e. moving into the finishing zone or shooting on goal). Thus, the model can accurately pinpoint the collective behaviors that the teams should avoid in order to ensure success.

The total number of passes and density were the most relevant variables in our model. Total passes was introduced in the study as a moderator variable to assess the specific influence of the network metrics on team performance. The improvement in the model obtained by adding the second block confirmed the metrics' specific influence. We observed a positive association between total passes and team performance. Each new pass in a set of offensive plays occurring within a 15 minute-period resulted in the teams being 8.2 % more likely to move into the finishing zone or to shoot on goal. The density of a ball-passing network increases whenever two players who were not yet connected pass the ball between them; in this way, high density is probably associated to high occurrence of these differentiated links. This greater variability of pass patterns, which is expressed in qualitatively distinct connections over a given period, may occur for different reasons. For example, greater collective dynamics and high player mobility can result in passes between players who regularly play in distant areas.

It has been shown that strong cooperation between teammates makes teams stronger and more successful (Balkundi & Harrison, Ties, leaders, and time in teams: strong inference about network structure's effects on team viability and performance., 2006). Thus, how can we explain our results showing that density has a negative effect (albeit small) on the successfulness of offensive plays? As can be seen in Figure 1, for density values ranging from 0 to 0.25 our model predicts mostly UOP outcomes. When we consider only events classified as SOP, there is a high number of offensive plays with density values ranging from 0.1 to 0.25, followed by a decrease. This drop in the number of offensive plays for higher density values could explain the negative association between density and SOPs. Indeed, despite being associated with fewer SOPs overall, higher densities are more likely to lead to SOPs (see Figure 2). Thus, our results suggest that density values lower than 0.25 are associated with a higher number of offensive plays, albeit mostly unsuccessful ones. Conversely, for density values above 0.25 there may be fewer offensive plays overall but most are successful. It is unlikely though that this negative association between density and SOPs is simply due to the higher number of errors and losses that result from the players' greater efforts to maintain connections in high-density scenarios (Burt, 1997). Instead, it seems more plausible that the reduction in SOP outcomes observed for density values above 0.25 explains that negative association. Indeed, these offensive plays with high-density values are characterized by a higher number of passes (see Figure 2), which could explain why there are fewer (but more successful) offensive plays in the same period of time. For example, these high-density values may result from longer ball-possession times, fewer ball possession losses, or specific losses in advanced zones of the field (finishing zone). This hypothesis is consistent with our observation that qualitatively differentiated links are associated with high densities, which likely reflects a greater unpredictability of passing patterns. Furthermore, it was previously proposed that greater variability of action and less exposure to the opponent could result from decentralized passing patterns (Gréhaigne, et al. (1997). Such characteristics of offensive plays associated with high-density values contribute to an offensive process that creates goal-scoring opportunities and are more effective for maintaining ball possession in advanced areas. Interestingly, offensive plays with similar characteristics have been observed in successful teams at the FIFA World Cup 2014 (Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015).

We found that the clustering coefficient is not a significant predictor of the successfulness of offensive plays, thus corroborating previous research (Gudmundsson & Horton, 2016; Peña & Touchette, 2012). However, our model indicates that a 10% increase in the clustering coefficient augments by 19.6% the probability of a SOP outcome (see also Clemente F. M., Martins, Kalamaras, Wong, & Mendes, 2015). High clustering coefficient values express the subgroup formation within the team itself; when these subgroups are created based on passes between teammates, as in the present study, the players performing in close areas tend to be linked together, thereby explaining the high clustering coefficients. This could reflect an offensive style choice based on short combinations between players, as previously observed for the Spain, Germany and Netherlands national teams at the FIFA World Cup 2010 (Peña & Touchette, 2012; Cotta, Mora, Merelo-Molina, & Merelo, 2011). Thus, the modest contribution of the clustering coefficient to the predictive value of our model suggests that different offensive styles may lead to successful team performance, depending, for example, on the players' individual qualities or on different strategic options. Further investigation is needed to clarify this issue.

Our results demonstrated that centralization is not consistently associated with successfulness of offensive plays, which is in agreement with findings by Fewell, et al. (2012) showing that there is no strong relationship between centralization and team performance. However, we found a positive effect of centralization on successful team performance, as a 10% increase in centralization increases by 20.8 % the chances of an SOP. This result contradicts a previous report showing that higher centralization is associated with worse team performance (goals scored) (Grund, 2012). This discrepancy could, however, be explained by the different methodologies in these studies, as discriminating successful and unsuccessful performances probably influenced the relationship between centralization and successful team performance in our study.

In summary, our results suggest that network density can accurately predict the ability of a team to enter the finishing zone or to shot on goal in elite football. Furthermore, this study gives new insights into the association between network density and team performance (Balkundi & Harrison, Ties, leaders, and time in teams: strong inference about network structure's effects on team viability and performance., 2006). First, we showed that low network density may be associated with a higher overall number of offensive plays but which are mostly unsuccessful. Second, high density was associated with fewer and/or longer offensive plays, which reduces the possibilities of a team moving into the finishing zone (hence decreasing total SOPs), thus resulting in a negative association between density and SOPs. Finally, we considered that high density may also be associated with fewer ball-possession losses before the teams reach the finishing zone (hence increasing probability of SOPs), thereby supporting the density-performance hypothesis.

We tested a model that analyzes the specific associations between the characteristics of a team's ball-passing network and the outcome of its offensive plays (entering the finishing zone and shot on goal vs losing ball possession). Previous studies had not differentiated these different outcomes, which may explain our results revealing a negative relation between density and team performance. Finally, we demonstrated that neither clustering coefficient nor centralization are significant predictors of team performance successfulness, possibly indicating that diverse offensive styles can be equally effective for a team to succeed.

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