

## Are the prominent players the most accurate and efficient? Study in football players from different competitive levels

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### Abstract:

The aim of this study was to study the association between technical performance (volume of play, efficiency index and performance score) and tactical behaviour (indegree and outdegree centrality) in different competitive levels of football. Sixty-six male soccer players (U12 – 11.23 ± 0.3 years old and 2.11 ± 0.9 years of practice; U14 – 13.43 ± 0.8 years old and 3.76 ± 2.4 years of practice; U16 – 15.67 ± 0.7 years old and 5.32 ± 1.3 years of practice; U18 – 17.84 ± 1.1 years old and 9.21 ± 2.2 years of practice; Amateurs with more than 20 years old – 23.45 ± 4.2 years old and 11.12 ± 2.7 years of practice) were observed in three official matches. The indegree centrality showed a large positive correlation with performance score ( $r = 0.630$ ;  $p = 0.001$ ) and very large positive correlation with volume of play ( $r = 0.735$ ;  $p = 0.001$ ). The outdegree centrality showed large positive correlation with volume of play ( $r = 0.535$ ;  $p = 0.001$ ), efficiency index ( $r = 0.590$ ;  $p = 0.001$ ) and performance score ( $r = 0.669$ ;  $p = 0.001$ ). In conclusion, this study revealed that the prominence in network activity might be associated with the technical performance in the match.

**Keywords:** graph theory; adjacency matrices; network analysis; technical performance; football.

### Introduction

The performance analysis in team sports has been used to identify how individual and collective behaviour emerges during competition (Filipe M Clemente, Couceiro, Fernando, Mendes, & Figueiredo, 2013). In the specific case of football, such analysis contributes to understand the specific variables that determine specific results (Gutiérrez-Díaz, González-Villora, García-López, & Mitchell, 2011).

In the specific literature of football, the physical variables have been exploited and well described in the last decades (Carling, Bloomfield, Nelsen, & Reilly, 2008; Carling, Reilly, & Williams, 2009). Nevertheless, there are a lack of articles that determines the technical and tactical variables in match (Filipe Manuel Clemente, Martins, Kalamaras, Wong, & Mendes, 2015; Hughes & Franks, 2005). In the case of technical analysis, the notational analysis and observational process have been the most common method to determine the individual performance (Sarmiento et al., 2014). Despite of this approach, recent studies have been introduced some protocols to determine the individual performance based on computational methods (Couceiro, Clemente, Martins, & Machado, 2014).

In the case of tactical behaviour and collective organization, some approaches have been working with observational protocols to determine the tactical knowledge, decision making and tactical behaviour of football players (Costa, Garganta, Greco, Mesquita, & Seabra, 2010; González-Villora, García-López, Pastor-Vicedo, & Contreras-Jordán, 2011; Gutiérrez-Díaz et al., 2011). Another approaches have been testing the collective organization of players based on spatio-temporal approaches (Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012; Filipe Manuel Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2014).

Despite of these investments in match analysis in football, there are no studies that associate different variables from technical and tactical point-a-view. For that reason, it is important to identify how technical variables may determine the tactical prominence of players based on a network approach. The network may determine the most prominent players and how teammates cooperates during the matches (Filipe Manuel Clemente, Martins, et al., 2015; Peña & Touchette, 2012). Thus, it is interesting to understand if the individual competency with ball may determine the capacity to be the central player in the network structure of the team.

Following the previous idea, this study aimed to associate technical and tactical variables in order to identify how such parameters may interact during official matches in different competitive levels and taking in account the different positional roles.

## Methods

### Participants

Sixty-six male soccer players (U12 – 11.23 ± 0.3 years old and 2.11 ± 0.9 years of practice; U14 – 13.43 ± 0.8 years old and 3.76 ± 2.4 years of practice; U16 – 15.67 ± 0.7 years old and 5.32 ± 1.3 years of practice; U18 – 17.84 ± 1.1 years old and 9.21 ± 2.2 years of practice; Amateurs with more than 20 years old – 23.45 ± 4.2 years old and 11.12 ± 2.7 years of practice) were observed in three official matches. All participants signed the Free and Clarified Consent Form according to the Declaration of Helsinki for the study in humans.

### Sample

A total of fifteen matches (three official matches per competitive level) from the Portuguese League were analysed and codified in this study. A total of 3.391 passes between teammates were collected and treated. From the observation, fifteen adjacency matrices were built and then processed in the scope of social network analysis.

### Data Collecting

The codification of tactical position it was the initial step during the data collecting. To do this, the codification it was based on the tactical lineup of the teams. For that reason, a techno-tactical assignment previously proposed it was adopted to positional roles (Di Salvo et al., 2007). The following codes were attributed to the tactical position: 1) goalkeeper (GK); 2) external defender (ED); 3) central defender (CD); 4) midfielder (CMF); and 5) forward (FW).

The network analysis it was made for each attacking unit of the observed team. A unit of attack it was considered from the moment of ball recovering until the team loses the ball. The passing sequence without interceptions it was recorded as an individual attacking unit. The linkage indicator between teammates it was the pass. Each attacking unit resulted in an weighted adjacency matrix and in the end of each match all adjacency matrices were converted in only one weighted adjacency matrix that represented the sum of all adjacency matrices occurred during the match. In the case of this observation, it was also considered the direction of the passes (A to B is different from B to A). For that reason the analysis it was based on weighted digraphs. This study followed similar protocols for social network analysis in football (Filipe Manuel Clemente, Martins, et al., 2015).

The same researcher made the fifteen observations. For that reason, only the intra-test of reliability it was performed. To do this, it was executed a test-retest process with 15% of the full data with 15-day interval. A value of 0.87 it was obtained from Cohen's Kappa test, thus revealing an appropriate margin for this procedures (Robinson & O'Donoghue, 2007).

### Technical Analysis

The analysis of technical level in match it was made using the TSAP protocol (Gréhaigne, Richard, & Griffin, 2005). In this protocol, five main indicators per players it were collected: i) conquered balls (CB) – balls recovered from the opponent; ii) received balls (RB) – passes received from teammates; iii) neutral balls (NB) – routine pass without progress in the field; iv) pass (P) – pass to a teammate that contributes to moving forward in the field; and v) shots on goal (SS) – shot to the opponent's goal.

Using these five technical indicators, three levels it were computed: i) volume of play ( $Volume\ of\ Play\ (VP) = CB + RB$ ); ii) efficiency index ( $Efficiency\ Index\ (EI) = \frac{P + SS}{10 + LB}$ ); and iii) performance score ( $Performance\ Score\ (PS) = \left(\frac{VP}{2}\right) + (EI \times 10)$ ).

### Network Analysis

To identify the tactical prominence of each player, two centrality metrics were used in this study. Both metrics were computed in the software SocNetV (version 1.8.). The SocNetV it is a specific software that it is used to process the network data based on Social Network Analysis (Kalamaras, 2014). The both metrics will be following introduced.

### Out-degree Centrality

The centrality level that determines how a player it is important to the passing sequence it is the OutDegree. The algorithm used to measure the %OdC it is (Opsahl, Agneessens, & Skvoretz, 2010):

$$C_i^{W(D-out)}(n_i) = \frac{k_i^{W-out}}{\sum_{i=1}^n \sum_{j=1}^n a_{ij}}, \tag{1}$$

that is the proportion of weights of nodes that are adjacent to  $n_i$ .

*In-degree Centrality*

The in-degree centrality (IDC) measure the in-degree of each node, which can be denoted by  $k_i^{in}$  or  $k_i^{W-in}$  (Wasserman & Faust, 1994). For the case of standardize the group size  $n$ , the %IdC may be computed as follows (Opsahl et al., 2010):

$$P_i^{W(D)}(n_i) = \frac{k_i^{W-in}}{\sum_{i=1}^n \sum_{j=1}^n a_{ij}}, \tag{2}$$

that is the proportion of weights of nodes that are adjacent to  $n_i$ .

*Statistical Procedures*

The relationship between network metrics (%InDegree and %OutDegree) and technical variables (volume of play, efficiency index and performance score) was investigated using Pearson product moment correlation coefficient. Preliminary analysis was performed to ensure no violation of the assumptions of normality, linearity, and homoscedasticity, as suggested by Pallant (Pallant, 2011). The following scales were used to classify the correlation strength (Hopkins et al., 1996): very small, 0–0.1; small, 0.1–0.3; moderate, 0.3–0.5; large, 0.5–0.7; very large, 0.7–0.9; 0.9–1, nearly perfect; 1, perfect. All statistical analyses were performed using IBM SPSS Statistics (version 22) at a significance level of  $p < .05$ .

**Results**

This study analyzed the network centralities and the technical efficacy of U14, U16, U18 and amateurs (more than 20 years old) in three official football matches. The descriptive statistics can be verified in the following Table 1.

Table 1. Descriptive statistics (mean and standard deviation) of network performance and technical efficacy per tactical position and competitive level.

	%InDegree		%OuDegree		Volume of Play		Efficiency Index		Performance Score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
U12										
GK	1.46	0.66	4.06	1.49	5.33	3.06	0.47	0.22	7.39	3.21
ED	8.55	1.83	12.32	1.99	33.67	9.87	1.21	0.30	28.92	7.16
CD	4.11	2.03	6.46	2.07	20.83	11.69	0.58	0.24	16.24	7.99
MF	12.97	2.78	12.34	2.04	52.78	10.74	0.68	0.16	33.20	5.81
FW	11.44	2.79	7.11	2.09	38.67	7.42	0.38	0.11	21.15	3.77
U14										
GK	2.17	0.79	4.84	1.67	7.00	2.65	0.28	0.27	6.32	2.67
ED	8.39	1.64	10.97	2.50	33.67	24.33	1.20	0.27	28.79	5.77
CD	4.97	1.19	6.60	1.13	24.33	7.37	0.36	0.17	15.77	4.27
MF	12.82	1.34	12.48	1.13	51.78	8.36	0.75	0.21	33.36	5.34
FW	10.90	2.34	7.53	1.31	39.22	9.08	0.36	0.13	23.17	5.17
U16										
GK	2.52	0.66	4.48	0.58	10.33	6.66	0.33	0.14	8.44	4.34
ED	8.00	1.36	11.62	1.31	39.33	8.59	1.23	0.24	31.92	5.77
CD	9.78	1.30	10.68	1.93	47.00	6.20	0.81	0.29	31.65	4.47
MF	12.38	1.15	11.84	1.36	60.89	10.02	0.85	0.29	38.98	6.59
FW	8.26	1.07	5.15	0.93	37.56	5.59	0.31	0.06	21.93	3.19
U18										
GK	2.15	1.70	4.58	2.52	7.00	6.25	0.27	0.18	6.23	3.21
ED	8.04	2.77	10.83	2.11	30.00	9.06	1.18	0.26	26.78	7.03
CD	5.68	2.87	8.06	2.05	26.50	2.52	0.65	0.16	19.76	6.98
MF	12.14	2.00	12.20	2.67	46.78	9.61	0.77	0.39	31.08	7.90
FW	11.31	2.64	7.04	1.68	35.33	8.25	0.39	1.014	21.55	4.07
Amateurs (more than 20 years old)										
GK	1.72	1.81	11.01	4.18	8.67	5.13	0.56	0.37	9.98	4.38
ED	13.47	3.23	15.70	3.96	34.00	9.19	0.87	0.20	25.73	5.53
CD	14.57	6.51	17.13	3.11	35.00	11.53	1.09	0.71	28.43	3.13
MF	19.37	2.59	15.02	2.22	43.17	3.55	0.64	0.32	28.03	3.66
FW	17.97	6.65	10.44	2.95	38.00	11.53	0.31	0.15	22.05	6.74

The relationship between network centralities (%InDegree and %OutDegree) and the characteristics of the technical efficacy (volume of play, technical efficiency and performance score) was investigated using Pearson product-moment correlation coefficient. The values of the coefficients are shown in Table 2.

Table 2. Correlation values between the network centralities and the technical efficacy – overall.

	%IdC	%OdC	VP	EI	PS
<b>Network Centralities</b>					
(1) %IdC: InDegree	1	0.640**	0.735**	0.077	0.630**
(2) %OdC: OutDegree		1	0.535**	0.590**	0.669**
<b>Network Performance</b>					
(3) VP: Volume of Play			1	0.279**	0.926**
(4) EI: Efficiency Index				1	0.621**
(5) PS: Performance Score					1

\* Correlation is significant at  $p \leq 0.050$ . \*\* Correlation is significant at  $p = 0.001$ .

The %IdC showed a large positive correlation with PS ( $r = 0.630$ ;  $p = 0.001$ ) and very large positive correlation with VP ( $r = 0.735$ ;  $p = 0.001$ ). The %OdC showed large positive correlation with VP ( $r = 0.535$ ;  $p = 0.001$ ), EI ( $r = 0.590$ ;  $p = 0.001$ ) and PS ( $r = 0.669$ ;  $p = 0.001$ ).

Based on the analysis per tactical position, it was carried out r-Pearson test organized per position. The results can be found in table 3.

Table 3. Correlation values between the network centralities and the technical efficacy – tactical position.

	%IdC	%OdC	VP	EI	PS	
<b>Goalkeeper</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.372	0.760**	0.289	0.722**
	(2) % OdC: OutDegree		1	0.326	0.666**	0.699**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.026	0.696**
	(4) EI: Efficiency Index				1	0.736**
(5) PS: Performance Score					1	
<b>External Defender</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.808**	0.472**	-0.278	0.211
	(2) % OdC: OutDegree		1	0.483	-0.079	0.306
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.500*	0.925**
	(4) EI: Efficiency Index				1	0.792**
(5) PS: Performance Score					1	
<b>Central Defender</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.936**	0.769**	0.280	0.723**
	(2) % OdC: OutDegree		1	0.671**	0.497**	0.735**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.316	0.920**
	(4) EI: Efficiency Index				1	0.663**
(5) PS: Performance Score					1	
<b>Midfielder</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.511**	-0.020	-0.200	-0.097
	(2) % OdC: OutDegree		1	0.044	0.387*	0.191
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.393*	0.928**
	(4) EI: Efficiency Index				1	0.708**
(5) PS: Performance Score					1	
<b>Forward</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.714**	0.416**	-0.078	0.364*
	(2) % OdC: OutDegree		1	0.252	0.195	0.287
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.129	0.962**
	(4) EI: Efficiency Index				1	0.394*
(5) PS: Performance Score					1	

\* Correlation is significant at  $p \leq 0.050$ . \*\* Correlation is significant at  $p = 0.001$ .

In the correlation of %IdC of goalkeeper it was found statistical very large positive correlation with VP ( $r = 0.760$ ;  $p = 0.001$ ) and PS ( $r = 0.722$ ;  $p = 0.002$ ). The %IdC of central defender revealed very large positive correlation with VP ( $r = 0.769$ ;  $p = 0.001$ ) and PS ( $r = 0.723$ ;  $p = 0.001$ ).

In the correlation of %OdC of goalkeeper it was found statistical large positive correlation with VP ( $r = 0.666$ ;  $p = 0.007$ ) and PS ( $r = 0.699$ ;  $p = 0.004$ ). The %OdC of central defender revealed large positive correlation with VP ( $r = 0.671$ ;  $p = 0.001$ ) and very large correlation with PS ( $r = 0.735$ ;  $p = 0.001$ ).

Table 4. Correlation values between the network centralities and the technical efficacy – competitive level

		%OdC	%IdC	VP	EI	PS
<b>U12</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.595**	0.870**	-0.012	0.755**
	(2) % OdC: OutDegree		1	0.674**	0.629**	0.808**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.191	0.939**
	(4) EI: Efficiency Index				1	0.517**
	(5) PS: Performance Score					1
<b>U14</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.688**	0.902**	0.207	0.795*
	(2) % OdC: OutDegree		1	0.731**	0.688**	0.850**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.350*	0.929*
	(4) EI: Efficiency Index				1	0.671**
	(5) PS: Performance Score					1
<b>U16</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.653**	0.912**	0.317	0.828**
	(2) % OdC: OutDegree		1	0.652**	0.782**	0.805**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.425*	0.937**
	(4) EI: Efficiency Index				1	0.714**
	(5) PS: Performance Score					1
<b>U18</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.611**	0.832**	0.106	0.692**
	(2) % OdC: OutDegree		1	0.688**	0.644**	0.804**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	0.338	0.920**
	(4) EI: Efficiency Index				1	0.680**
	(5) PS: Performance Score					1
<b>Amateurs (&gt; 20 years old)</b>	<b>Network Centralities</b>					
	(1) % IdC: InDegree	1	0.414	0.957**	-0.185	0.745**
	(2) % OdC: OutDegree		1	0.555**	0.457*	0.731**
	<b>Network Performance</b>					
	(3) VP: Volume of Play			1	-0.060*	0.849**
	(4) EI: Efficiency Index				1	0.477*
	(5) PS: Performance Score					1

\* Correlation is significant at  $p \leq 0.050$ . \*\* Correlation is significant at  $p = 0.001$ .

Significantly very large correlations were found in %IdC of U12 with VP ( $r = 0.870$ ;  $p = 0.001$ ) and PS ( $r = 0.755$ ;  $p = 0.001$ ). In U14 competitive level, significantly nearly perfect correlations were found in %IdC with VP ( $r = 0.902$ ;  $p = 0.001$ ) and very large positive correlations with PS ( $r = 0.795$ ;  $p = 0.001$ ). Significantly nearly perfect correlations were found in %IdC of U16 with VP ( $r = 0.912$ ;  $p = 0.001$ ) and very large positive correlations with PS ( $r = 0.828$ ;  $p = 0.001$ ). Very large positive correlations were found in U18 between IdC and VP ( $r = 0.832$ ;  $p = 0.001$ ) and large positive correlations between IdC and PS ( $r = 0.692$ ;  $p = 0.001$ ). In Amateurs with more than 20 years old it were found statistically nearly perfect correlations between IdC and VP ( $r = 0.957$ ;  $p = 0.001$ ) and very large positive correlations between IdC and PS ( $r = 0.745$ ;  $p = 0.001$ ).

Significantly very large positive correlations were found in %OdC of U12 with PS ( $r = 0.808$ ;  $p = 0.001$ ) and large positive correlations with VP ( $r = 0.674$ ;  $p = 0.001$ ) and EI ( $r = 0.629$ ;  $p = 0.001$ ). In U14 competitive level, significantly very large positive correlations were found in %OdC with VP ( $r = 0.731$ ;  $p = 0.001$ ) and PS ( $r = 0.850$ ;  $p = 0.001$ ) and large positive correlations with EI ( $r = 0.688$ ;  $p = 0.001$ ). Significantly very large positive correlations were found in %OdC of U16 with EI ( $r = 0.782$ ;  $p = 0.001$ ) and PS ( $r = 0.805$ ;  $p = 0.001$ ) and large positive correlations with VP ( $r = 0.652$ ;  $p = 0.001$ ). In U18 competitive level, significantly very large positive correlations were found in %OdC with PS ( $r = 0.804$ ;  $p = 0.001$ ) and large positive correlations with VP ( $r = 0.688$ ;  $p = 0.001$ ) and EI ( $r = 0.644$ ;  $p = 0.001$ ). Finally, in Amateurs with more than 20 years old it were found statistically very large positive correlations between IdC and PS ( $r = 0.731$ ;  $p = 0.001$ ) and large positive correlations between IdC and VP ( $r = 0.555$ ;  $p = 0.009$ ).

## Discussion

In this study it was analysed the association between technical indicators of performance and tactical prominence inspected by social network analysis. The variables of tactical position and competitive levels were considered in the moment of split the correlation analysis.

In a general analysis, it was found that indegree centrality had statistically correlations with volume of play and performance score. In other hand, outdegree centrality had statistically correlations with volume of play, efficiency index and performance score. This result can be explained by the fact that outdegree centrality reveals the player with greater centrality in to pass for the teammates and in to build the attacking process (Filipe Manuel Clemente, Couceiro, Martins, & Mendes, 2015). For that reason, such player must have a great technical efficiency justified by the number of successful actions performed. In another perspective, the indegree centrality reveals the player with greater centrality in to receive the ball. For that reason, one player may be the focus of the team but may reveal a small efficiency in the moments with ball. In one example, the striker may receive more balls than the remaining teammates but may lose the majority of possessions and for that reason have a small value of technical efficiency.

In the analysis made by tactical position, it was possible to observe that central defender had the greater value of correlation of indegree centrality with volume of play and performance score. By other hand, in external defenders and midfielders the values of indegree centrality had very small correlations with all technical indicators. This may suggest that another technical scores that were not analysed during this study may justify the tactical prominence of midfielders. The same evidences were found in the outdegree centrality. These results may suggest that the activity of midfielders and external defenders and their influence in the network structure of the team may not exclusively depend from their technical efficacy.

Finally, the comparison between competitive levels revealed that indegree centrality had larger correlation values with volume of play and performance score and small correlation values with efficiency index, following the general analysis. In the case of outdegree centrality, it was found large and very large correlation values with all technical indicators in the majority of competitive levels, suggesting that the structure of activity between different levels it is similar.

This study had some limitations. The sample it is too small to generalize the findings. Moreover, the relative values of the network algorithms may constrain the outputs based on the fact that the results only vary between the limits. In future studies, it is very important to increase the number of analysed matches and also to use algorithms without relative algorithms in order to identify differences between competitive levels and tactical positions.

## Conclusion

In this study it was found that generally the volume of play has greater correlation values with indegree centrality during football matches of different competitive levels. In other hand, the outdegree centrality has greater correlation values with performance score. These evidences were observed in competitive levels from under-12 until amateurs with more than 20 years old. Such results may indicate that the technical performance in match may lead with greater tactical prominence in the network activity during attacking moments in football.

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