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Dünya Kupası'nda takım sıralaması ve maç performansı analizi

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ÖZET

Son yıllarda futbolda maç performansı verileri kullanılarak performansın değerlendirilmesine yönelik çalışmalara sıklıkla rastlanmaktadır. Ayrıca çoğu çalışmada tek boyutlu bir yaklaşımın kullanıldığı ve maç performansı değişkenlerinin maç üzerindeki etkilerine ilişkin görüşlerin dile getirildiği görülmektedir. Bu çalışmada, 2018 Dünya Kupası'nda maç sonucunu etkileyen performans göstergelerinin faktör analizi yoluyla retrospektif yöntem kullanılarak belirlenmesi ve turnuvanın bu değişkenlere göre yeniden sıralanması amaçlandı. Çalışmada 2018 Dünya Kupası'nda 32 takımın toplam 64 maçına ait 16 farklı maç içi performans verisi kullanıldı. Elde edilen bulgulara göre başarılı pas yüzdesi, şut sayısı ve kaleyi bulan şut sayısı değişkenleri arttıkça takım başarısının da buna bağlı olarak arttığı, ayrıca takımın savunmaya katkısının da başarı oranını arttırdığı görülmüştür. Öte yandan ofsayt ve top kaybı arttıkça takımın başarısının düştüğü de görüldü. Bu durumda takımların başarısı, takımın hücum ve savunma yapısının iyi dengelenmesi gerektiğini gösteriyor. Çalışma sonucunda ilk faktör olarak sunulan hücum ve savunma performans oranları birbirine yakın olan takımların ilk 4'e girmesi durumunda maç içi performans verilerinin takım sıralamasına katkı sağlayacağı düşünülmektedir.

Anahtar Kelimeler: Dünya kupası, faktör analizi, futbol, takım sıralması

The team ranking and match performance analysis in WORLD CUP

ABSTRACT

In recent years, studies on the evaluation of performance by using match performance data in football can be frequently encountered. It can also be seen that most studies have used a one-dimensional approach and expressed opinions about the effects of the match performance variables on the match. In this study, it was aimed to determine the performance indicators affecting the match result in the 2018 World Cup over factor analysis, using a retrospective method and to re-rank ranking the tournament with these variables. In the study, we used 16 different in-match performance data for a total of 64 matches of 32 teams in the 2018 World Cup. According to the findings, it was seen that when the variables of successful pass percentages, the number of shots and the number of shots on target increased, team success increased accordingly, and also the contribution of the team in defense also increased the success rate. On the other hand, it was also seen that as the offside and turnover increased, the success of the team decreased. In this case, the success of the teams indicates that the offensive and defensive patterns of a team should be well balanced. As a result of the study, it is thought that when teams with close offensive and defensive performance ratios, which are presented as the first factors, are among the top 4, the in-match performance data contributes to the team ranking.

Key Words: World Cup, factor analysis, football, team ranking, soccer

Introductions

Football, the most mentioned field of sport with its name and content, is reaching more and more people day by day, a phenomenon significantly contributed by FIFA so much so that FIFA has become one of the largest sports federations in the world with its members from 211 countries. The football organization known as the World Cup is organized by FIFA in every 4 years. The first World Cup tournament was held in Uruguay in 1930 with the participation of 13 countries. The organization was suspended from 1942 until 1950 due to World War II. 21 tournaments have been organized so far, with 8 different national teams winning the World Cup. The World Cup is the most important tournament in football and offers the opportunity to examine the best national teams and players in the world. Of course, researchers could not remain indifferent for such a large sports branch and a wide spread of organizations.

Especially in recent years, there has been an increase in the number of researches on the evaluation of technical-tactical performance using match data at the team and player level. Statistical analysis of performance based on match data appears to be frequently used in team sports and individual sports, including football (Falco et al.2012; García et al.2013; Hughes and Bartlett 2002; Miarka et al.2016; Stutzig et al.2015; Travassos et al.2013). There is a strong relationship between football and statistics as a science, with its dating back very long. For many years, a great deal of data has been collected on and off the field, providing information about both teams and players. Especially in recent years, in addition to anthropometric, psychological and physiological research; technical and tactical analysis of football players' performance on the field have come to become popular (Goes et al.2020; Gonzalez-Rodenas et al.2020; Lorenzo-Martínez, Rey, and Padrón-Cabo 2020; Pino-Ortega et al.2021).

Analyzing the performance of football teams provides quantitative and tangible data both for club and team managers. Team-related strategy can be quite a determinant factor in making forward-looking decisions on such issues as the selection of players, coaches or tecnical directors. With the advent of technological innovations, the amount of these data is increasing day by day. Nowadays, with the development of video, data collection and computer science technology, companies such as OPTA, Wyscout, Instat can provide detailed and diverse data such as spatial-temporal information and technical-tactics of the players. Thanks to these data sets, studies that quantify certain aspects of football performance have emerged (Gonçalves et al.2019; Low et al.2020; Oberstone 2011; Tunaru and Viney 2010). It is observed that attaching importance to statistical results in evaluating both individual and team performance yields positive outcomes. The increase in the amount of data and the emphasis on statistical results, on one hand, has caused an increase in the number of studies carried out benefiting from these data, and on the other hand, new alternatives have showed up in addition to the traditional statistical methods used on football data for years.

In this study, rearranging an alternative tournament success ranking based on various performance variables exhibited during the matches of the teams participating in the 2018 World Cup in addition to the differences of these performance criteria compared to the actual tournament ranking using the factor analysis method were examined.

Material and Method

A total of 32 teams participated in the 2018 World Cup tournament, out of which 8 groups were formed with the participation of Belgium, Brazil, Croatia, England, France, Spain, Germany, Uruguay, Sweden, Argentina, Russia, Japan, Switzerland, Portugal, Mexico, Denmark, Colombia, Tunisia, Senegal, Republic of Korea, Iceland, Peru, Morocco, Saudi Arabia, Costa Rica, Nigeria, Serbia, Panama, Poland, Australia, Egypt and Iran. After the group matches, a round of 16 teams consisting of group-winners and runners-up went through qualifying competitions and the winning teams qualified and continued to the tournament. 128 matches were played during the tournament.

Performance indicators

The data for these players were obtained from OPTA Sports Data (OPTA, 2020). Data reliability and validity of OPTA Client system were studied by (Liu et al. 2013). Many papers based on OPTA data have been published (Gai et al. 2019; Konefał et al. 2018; Lago-Peñas et al. 2016; Oberstone 2011b; Tunaru and Viney 2010). The definitions of the technical terms can be accessed from the web page for OPTA sports (OPTA, 2020) In the study, 16 different in-match performance criteria in the matches played by the teams participating in the World Cup tournament were considered which are;

X1:… Shot on Target: It is the division of the number of shots on target by the players of a team during the matches they play in a championship by the total number of matches played by that team.

X2:… Ball Possession: This is the division of the percentage of players of a team possessing the ball in their feet during the match by the total number of matches played by that team. X3:… Shot Taken (Including the blocked ones): It is the division of the shots taken by the players of a team during the matches played in the tournament by the total number of matches played by that team. (Blocked shots are also included in this variable.) X4:… Pass: The division of number of times a team's players pass the ball to their own team players during the matches played in the tournament by the total number of matches played by that team. X5:… Successful Pass: The division of the number of times a team's players can send the ball to their own team players accurately and successfully during the matches played in the tournament by the total number of matches played by that team. X6:… Scored Goal: It is the division of the goals scored by the players in the matches played by a team in the tournament by the total number of matches played by that team. (Penalty goals are also included in this variable.) X7:… Corner: It is the division of the number of corner kicks of a team by the total number of matches played by that team. . X8:… Goal Pass (Assist): It is the division of the number of passes forwarded by the players of a team to their teammates during the matches played in the tournament resulting in a goal by the total number of matches played by that team. X9:… Goals Conceded: It is the division of the number of goals a team concedes in the matches played in the championship by the total number of matches played by that team. X10:… Goal Prevented: The division of the number of times the goalkeepers of a team prevented the opposing team from scoring the goal by the total number of matches played by that team (Penalties saved are also included in this variable.) X11:… Offside: It is the division of the moment when the defense suddenly comes forward and leaves the opponent team players in offside position as the opponent's player is waiting for a pass by the total number of matches played by that team .X12:… Cross: It is the division of the number of

long passes a team intends to reach into the penalty area of the opponent from inside the pitch during a tournament by the total number of matches played by that team. X13:… Turnover: It is the division of a team's player to lose the ball to a player of the other team by the total number of matches played by that team. X14:… Fouls Committed: It is the division of the total number of fouls committed by a team against the opposing teams by the total number of matches played by that team. X15:… Struggle (Tackle): It is the division of the moment when the ball in the possession of an opponent player is taken away by a player from the other team by the total number of matches played by that team .X16:… Fouls Won: The division of the number of fouls won by a team by the total number of matches played by that team. The data used in this study includes statistics on the matches of the teams in the 2018 World Cup and does not contain data of any football player. This study was approved by the Ethics Committee of the Dokuz Eylul University Izmır, Turkey.

Statistical analysis

The independent variables determined within the scope of the study were categorized as a result of the match analysis. Within the scope of the data collected, it was decided to select the most likely variables that could have an effect on the team ranking. SPSS 25 package program was used in the statistical analysis of the research data, and Factor Analysis was applied to determine the variables affecting the result. The strength of the relationships between variables was analyzed with Kaiser-Meyer-Olkin (KMO).

Then, factor analysis was conducted to re-rank the tournament results according to the match performance data. Factor analysis is a data reduction method. Instead of working with a large number of variables, it gathers more similar ones together and enables working with a small number of factors. In this way, analyzes are visualized, ease of interpretation is provided, thus more accurate and significant results are achieved. There are four stages in the implementation of factor analysis which can be listed as; the extent to which the data sets are suitable for analysis, the supply of the factors, the rotations of the factors and their acquisition accordingly.

There are different stages for factor analysis to take place. In the first place, descriptive statistics are needed. Descriptive statistics provide a visual summary of the variables. At the same time, the normal distribution of the data is an important assumption in terms of making the factor analysis more accurate. After the tabulation of variables and data, the suitability of the data for analysis should be checked. Keiser Meyer Olkin-Bartlett tests are applied to reveal whether the data are suitable and sufficient for analysis.

$$KMO = \frac{\sum_{i \neq j} \sum r_{ij}^2}{\sum_{i \neq j} \sum r_{ij}^2 + \sum_{i \neq j} \sum a_{ij}^2}$$

If the KMO value is above 0.50, it indicates that the data is sufficient, and if the Bartlett's test result is $p = 0.000 < 0.05$, it indicates that the data is suitable for factor analysis. Table 1

Table 1. Recommended Criteria for Kaiser-Meyer-Olkin Testing

KMO	
0,90+	Marvelous
0,80+	Meritorious
0,70+	Middling
0,60+	Mediocre
0,50+	Miserable
0,50-	Unacceptable

It is calculated by taking a value of 1 for the lambda value (ʎ), assuming that all values are common. After the factor is extracted, the common variance results are expected to be above 0.50.

Then, eigenvalues and slope plots are employed to determine the number of factors. By using the extracted factors, rotation process is applied while naming the factors. The purpose of rotation is also to determine which data is collected under which factor. Within the scope of the research, it provides estimated rankings by using the factor results.

Factor Analysis Model

A new factor formation, independent from each other, is performed from the data sets connected with each other within the frame of p. This method, which is created by using the covariance or correlation matrix, is defined as the exploratory factor analysis. With this analysis, the factors with a more independent position than the variable with an original structure that is determined as p are detected. By considering the coefficients of these determined factors, a new score not related to each other is created.

$$Z_J = a_{j1}f_{1+}a_{j2}f_{2+\cdots}a_{jm}f_{m+}b_ju_jj = 1,2,\ldots.,p$$

ZJ : Jth variable

Ajm : The load of the Jth variable on the Mth factor

F: common factor

Uj : custom or residual factor

Bj : coefficient for special or residual factor

Figure 1 shows the sample model used in the research for factor analysis. This exemplary model has two factors symbolized as latent variables. The arrow connecting the factors between the latent variables shows the variance or covariance between the

latent variables. The areas marked with an X represent each indicator. One-way arrows from factors to indicators show the direct effect of that indicator on that factor. The direct effect shows the factor load value in the exploratory factor analysis. When Figure 1 is examined, it can be seen that the measurement errors existing in every measurement is indicated by E.

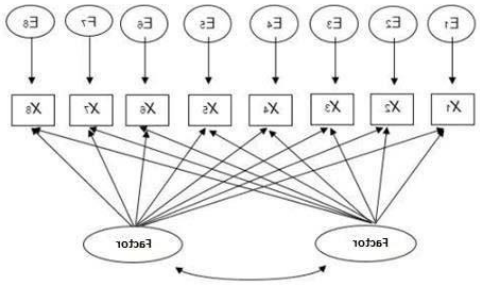

Figure 1. Factor Analysis Model

Results

Descriptive statistics of the data were determined before performing the Factor Analysis. Descriptive statistics are made to present all these results through tables or figures following the averaging, classification and calculation of the prevalence measurements. Such descriptive statistics as means, standard deviations, frequencies, and percentages were used to analyze the data Table 2.

In Table 2, the mean shooting accuracy of the teams during the tournament was found to be 15.81 ± 9.26. Here, the minimum value is 4, which belongs to the Iranian team, while the maximum value is 40, which belongs to the Belgian and Brazilian teams, which shows that Iran is not good at forwarding pass.

Table 2. Descriptive Statistics

	$\bar{x}$	SS	Min	Max
Shot On Target	15,81	9,265	4	40
Ball Possession	49,00	10,82	26,45	74,67
Shot	50,72	25,33	23	113
Pass	1851,81	882,42	647	3840
Successful Pass	1519,06	790,40	405	3276
Goal	5,28	4,066	2	16
Corner	18,84	9,978	5	41
Assist	3,25	2,759	0	12
Goals Conceded	5,28	2,203	2	11
Saved	10,75	5,809	1	27
Offside	5,34	3,001	0	15
Cross	45,97	23,14	18	134
Challenge Lost	532,25	192,17	315	1126
Fouls Committed	54,13	20,76	29	112

Tackle	40,69	13,88	24	80
Foul Won	51,53	22,25	22	107

Table 3. KMO and Bartlett Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		,816
Bartlett's Test of Sphericity	Approx. Chi-Square	803,125
	df	120
	Sig.	,000

As can be seen in Table 3, it can be said that our data is sufficient since the KMO value is 0.816 (over 0.50). Bartlett's test result was p = 0.000 <0.05, revealing that our data is significant. The results of both tests indicate that the data are suitable for factor analysis.

As seen in Table 4, it is calculated by taking the value 1 for ʎ, assuming that all values are common. After the factor is extracted, the common variance results are expected to be above 0.50. It can be observed that the pass values have the highest common variance values, while the offside values have the lowest common variance value. In this case, it causes offside values and clearance values to be considered separately from other variables. The reason for this finding is that it is not considered as either offensive or defensive when it is divided into factors.

Table 4. Variance

	ʎ	Extracted
Shot On Target	1,000	,869
Ball Possession	1,000	,839
Shot	1,000	,943
Pass	1,000	,956
Successful Pass	1,000	,948
Goal	1,000	,929
Corner	1,000	,847
Assist	1,000	,833
Goals Conceded	1,000	,916
Saved	1,000	,553
Offside	1,000	,526
Cross	1,000	,747
Challenge Lost	1,000	,901
Fouls Committed	1,000	,916
Tackle	1,000	,806
Foul Won	1,000	,807

In the factor analysis, as a result of the Varimax rotation method, -accepted as the orthogonal rotation method and applied in order to prevent a possible relationship

between them, aiming to distribute the factors in which the variables were separated independently from each other-, 3 factors for which a eigenvalues matrix greater than 1 were determined in the factor analysis as shown in Table 5.

In order to determine the number of suitable factors, the eigenvalues, the part of the total variance explained by the factors, or the slope plot revealed by the eigenvalues were examined. Figure 2 is a graphical representation of the determined factors. As can be seen in Figure 2, the eigenvalue (ʎ) in the slope graph was accepted as above 1 and 3 factors above 1 were determined. For this reason, the factor analysis to be made should consist of denomination of the 3 factors.

The purpose of rotation is to determine which data are collected under which factor, and to ensure that the factors are interpretable and significantly available. Weights above 0.50 are considered quite well.

Table 5. Total Variances Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10,51	65,68	65,684	,51	65,68	65,68	,85	36,55	36,55
2	1,802	11,26	76,94	,802	11,26	76,94	,291	33,06	69,62
3	1,024	6,402	83,351	,024	6,402	83,351	,196	13,72	83,351
4	,679	4,242	87,594						
5	,605	3,782	91,376						
6	,416	2,602	93,977						
7	,263	1,644	95,622						
8	,225	1,405	97,026						
9	,154	,964	97,991						
10	,113	,708	98,699						
11	,077	,484	99,183						
12	,068	,427	99,610						
13	,035	,216	99,826						
14	,019	,121	99,947						
15	,008	,053	99,999						
16	0,00009	,001	100						

Figure 2. Scree Plot

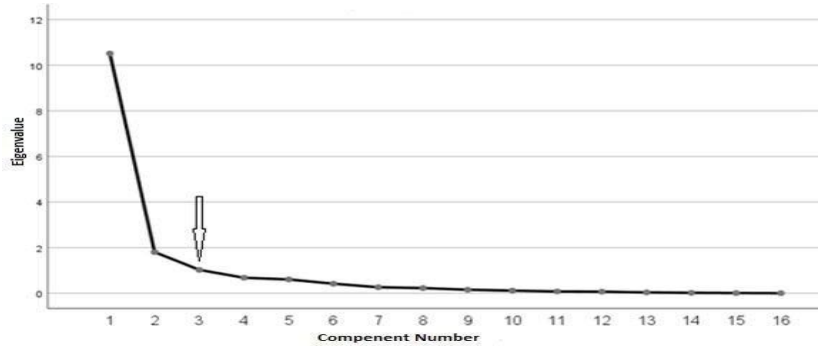

Table 6. Component Matrix

	Component		
	1	2	3
Successful Pass	,831		
Ball Possession	,813		
Shot	,808		
Pass	,801		
Shot On Target	,782		
Corner	,777		
Cross	,702		
Fouls Committed		,926	
Challenge Lost		-,774	
Goal		,764	
Tackle		,764	
Saved		,715	
Asist		,712	
Foul Won		,584	
Goals Conceded			-,955
Offside			-,535
Extraction Method: Principal Component Analysis Rotation Method Varimax with Kaiser Normalization			
a. Rotation converged in 4 iterations			

As shown in Table 6, successful pass (0.831), ball possession (0.813), total shots taken (including blocked ones) (0.808), pass forwarded (0.801), shot on target (0.782), corner (0.777), cross (0.702) were loaded on the first factor, while foul committed (0.926), turnover (-0.774), goals scored (0.764), struggle won (0.764), goal prevented (0.715), goal assist (0.712) and foul won (0.584) are loaded on second factor and also the goals conceded (-0.955), and offside (-0.535) were loaded on the third factor.

Table 7: 2018 World Cup Rank and re-Ranking

	FIFA		Factor Analysis	
Country	Tournament Ranking	All time rank	Factor 1	re-Ranking
Belgium	3	3	0,993	6
Brazil	6	2	2,467	1
Croatia	2	20	1,224	4

England	4	12	1,206	5
France	1	7	0,458	10
Spain	10	10	2,174	2
Germany	23	1	1,666	3
Uruguay	5	14	0,506	9
Sweden	7	24	-0,377	20
Argentina	15	5	0,592	8
Russia	8	70	-1,027	29
Japan	16	61	-0,116	16
Switzerland	13	6	0,593	7
Portugal	14	4	0,307	11
Mexica	11	15	-0,518	22
Denmark	12	12	-0,291	18
Colombia	9	16	-0,023	14
Tunisia	24	21	-0,913	27
Senegal	17	27	-0,594	24
Korea	19	57	-0,919	28
Iceland	28	22	-0,908	26
Peru	20	11	0,066	13
Morocco	27	41	-0,386	21
Saudi Arabia	26	67	0,167	12
Kosta Rika	29	23	-0,905	25
Nigeria	21	48	-0,320	19
Serbia	22	34	-0,543	23
Panama	32	55	-1,901	32
Poland	25	8	-0,084	15
Australia	30	36	-0,287	17
Egypt	31	45	-1,032	30
Iran	18	37	-1,275	31

The first column of Table 7 contains the names of the teams, the second contains the success rankings of the teams in the 2018 World Cup, and the general rankings of the teams for all time in 2018 by FIFA are presented in the third column. Also, the fourth column contains the first factor scores with the highest explanation rate, while the fifth column contains the rankings in the first factor. According to the analysis performed, since the variation intervals of the variables used in the first factor were different from each other (for example, the minimum value of the successful pass variable was 405, the maximum value was 3276, the total successful pass and the percentage of ball possession was measured as a minimum of 26.45 and a maximum of 74.67) factor loads were obtained by calculating the scores.

Discussion

In this study, factor analysis was carried out by using Opta data of the ranking of the teams in the 2018 World Cup, and the ranking of these factors in the World Cup was rearranged again. As a result of the findings obtained from the study, the most important possible success criterion affecting the tournament result seems to be the goals scored by the teams.

According to the findings, another variable stands out, apart from the goals scored by the teams. It is thought that the percentage of passes made by the teams during the match increases the importance of the contribution of the team in defense. In this case,

the success of the teams indicates that the way teams maintain offense and defense should be well balanced. Li et al. (2020) also found in their study on the Chinese super league that the pass success and shot on target in penalty positively affected the team rankings in the league. Another study conducted to determine the number of goals and match results in football provides results supporting our study (Goddard 2005).

According to the findings of another study on the use of match statistics that discriminate between successful and unsuccessful soccer teams, the variables related to offensive play were identified as total shots, dangerous shots and possession of ball (Castellano, Casamichana, and Lago 2012). In fact, the fact that teams with close offensive and defensive performances are in the top 4 in the study also explains this situation. In practice, countries have their own play styles and tactical understandings.

The variables included in the analysis show the skills and performance of the teams in the matches. After separating the variables into factors, Successful Passing, Ball Possession, Total Shots, Pass, Shots on Target, Corners and Crosses into the penalty area constitute the first factor. The first factor can also be called the offense factor, since it is related to the offensive positions of the teams under this factor. In a study conducted on Spanish and English leagues, evidence was presented showing that a playing style of a team is defined by certain performance indicators and as a result, teams can be classified to create a playing style profile (Fernandez-Navarro et al.2016).

When the Gülel and Telligolu's study (2016) study is examined, it can be seen that the 2014 world cup champion Germany was ranked 5th according to the first factor, Argentina was the second, and the Netherlands ranked 19th. In the study, as a result of the ranking made according to the first factor (offense factor), the 2018 World Champion team France was ranked 10th according to the offense performance, Croatia the runner-up was the 4th, and Belgium, the 3rd, was ranked as the 6th. Britain, which ranked the fourth in the tournament, was ranked the 5th.

According to this factor, which is called the first factor, it has been concluded that the factor result is different from the rankings made in the World Cup in both studies. It should not be forgotten that the rankings revealed in the study were included in the Opta data, in other words, the performances of the teams during the matches during the tournament, which were used in the analysis.

It was estimated based on the first factor analysis that the team that would complete the tournament as the champion was Brazil, Spain the second, Germany the third and Croatia as the fourth, based on the offensive performances among the teams in the World Cup. On the other hand, looking at the overall factor (both offensive and defensive balance) rankings of the teams in the World Cup, it was shown that Croatia might finish the tournament as champion, England as the runner-up, Belgium the third and France as the fourth. In the study by Gülel and Telligolu 2016, the analysis was made according to variables in various areas such as defensive actions (loss, tackle), penalties (yellow card, red card, foul) in addition to the goal. In our study, the analysis was created on the basis of such variables as Foul, Turnover, Struggle Won, Preventive and Offensive actions, which are shown as defensive actions exhibited as a team, such as Goals, Assists and Fouls Won. Analysis of match statistics from the group stage of the 2014 Brazil FIFA World Cup revealed several key factors influencing the likelihood of winning. The data indicated that nine specific statistics positively impacted the probability of victory: Shots,

Shots on Target, Shots from Counter Attacks, Shots from Inside the Area, Ball Possession, Short Passes, Average Pass Streak, Aerial Advantage, and Tackles. Conversely, four statistics were found to negatively affect winning chances: Shots Blocked, Crosses, Dribbles, and Red Cards. An additional twelve statistics showed either negligible or indeterminate effects on the outcome of the games (Liu et al 2015).

Conclusion

This study consisted of remodelling the tournament rankings according to various in-match performance variables of the teams in the 2018 World Cup using factor analysis. It has been determined that a team with a good offensive power in a tournament may be higher in the rankings, but it is not enough for a team to be successful alone. In this case, the fact that the defense strength is good in addition to the offensive strength affects the tournament success of the team, but it shows us that it will not be enough alone in reaching the championship.

Also, considering the signs of the factor loadings, Goals Conceded, Offside and Turnover are marked as negative. As it can be understood from here that the success of the team decreases as the Goals Conceded, Offside and Loss of Ball increase. As the Possession, Corners, Successful Passes, Total Shots, Passing, Shot Accuracy, Goals, Struggle Won, Goal Prevention, Assists and Fouls Won increase, the success of the team increases accordingly.

The fact that Successful Pass, Possession, Total Shots (Including Blocked), Shot on Target, Corner, Crosses are related to Goals and Assists or that they are not in the same factor, though interrelated with an effect on each other (for instance; the passes made may be due to the presence of the side passes and back passes) shows that goal and assist will not occur just as a result of the exchange of passes. Therefore, although the first factor value is the offensive performance of the teams, it was aimed to predict what the team that could only score the goal without the presence of goal and assist values could do by incorporating what they did before the action started. The reason why the second factor also includes the values of Struggle, Clearance, Foul Won, Turnover, Foul Committed is thought to be due to the fact that with Goals and Assists, which may be due to the fact that winning the set ball before scoring is the final position before scoring a goal as the likelihood of scoring a goal is increased due to the higher probability of winning a set ball in a foul won by teams.

Based on the results of this study, it is a clear for future studies that a more detailed analysis will be effective by adding variables related to the way the teams spread on the pitch, the total distance traveled, as well as the number of turnovers as they go on the offensive and the time to get the lost ball back. As a technological framework, methods developed with machine learning and artificial neural networks can provide depth and substantiality for this type of study.

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