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Discovering primary indicators for evaluating defender's technical performance using multivariate statistics in football games

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Abstract

The purpose of this study is to examine primary indicators for evaluating the defenders' technical performance in football games. We collected a total 472 players' match statistics of season 2017/2018 in tier 1 league of England, Spain and Germany and categorized them into central and wide. Principal component analyses are used to sort the indicators and using eigenvalues for an appropriate number of components. The results showed that "Tackles Lost", "Defensive Errors" and "Errors Leading to Goal" were the primary indicators for central defenders and "Successful Take-on", "Total Shots" and "Errors Leading to Goal" were crucial for wide defenders.

Key words: Football, Technical Performance, Defenders, Principal Component Analysis, Exploratory Factor Analysis

Introduction

Due to the expectation of highly professionalized players, analyzing big data of professional football has arisen tremendously. Since more data of high-performance football has been accumulated, data analysis with event data (goals, passes, tackles etc.) has been done for many years (Memmert, 2018). The development of big data and analysis systems has been conducted to understand better football in terms of performance analysis (Rein, 2016).

Various methods and approaches were taken to find a more objective way of describing a football team or individual performance. Rösch et al. (2000) mentioned that physical condition, technical performance, and tactical performance are the three most important variables for measuring performance in team sports. Key performance indicator (KPI) is used to simplify an

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intricate system to simple numbers for rating or ranking. It is easy to find KPI of single athletes whose performance can be measured with simple numbers such as the speed of runners. However, football is a complicated sport that combines many components for a performance like technical or tactical area which makes it difficult to define KPI (Perl, 2018). Despite the difficulties in measuring KPI of football, many scientific approaches have been introduced for performance analysis with match statistics from football (Perl, 2018; Yang, 2018).

Many efforts have been made to evaluate and compare individual football player’s physical and technical performance with KPI. Comparing the difference in physical and technical skills of domestic and foreign players by positions with match statistics in the China Super League showed that which skills domestic players should have to a become better player. Players from different positions showed differences not only in physical demands but also in technical skills (Gai et al., 2019). Using the indicators selected by professional coaches and match analysts, Taylor, Mellalieu and James (2004) made inter- and intra-positional comparisons to compare each positions’ characteristics. Bush et al. (2015) checked the development of the players’ physical and technical parameters by investigating the statistics throughout five seasons and resulted that each position requires different parameters such as physical demands for a wide player and technical demands for center player. These studies suggest a well-recognized fact that players need to be evaluated on different standards according to their positions. This is largely because since players serve different roles in the field, and thus, show different ranges in many technical indicators.

Although differences in technical indicators of different positions are required, present studies suggest limitation of using same indicators. You (2013) selected six factors that can be used to evaluate a player’s performance and weighed their significance different with each position using the fuzzy analytic hierarchy process. Hong (2010) also made the same division, only focusing on the technical indicator difference among the positions. He also stated that all players should not share a common criterion for evaluation, but different standards.

On the other hand, many media in today’s football society try to make a player’s performance evaluation through technical approaches. Using technical indicators such as shots, passes, tackles etc., the media developed their rating systems. To calculate a player’s performance based on their statistics, Whoscored(2019) developed comprehensive statistical algorithm. Aside from the rating systems of media, the recent CIES Football Observatory report (Poli, 2018) also identified 6 factors and 14 sub-factors for technical analysis of football player performance.

These literature studies and media used multivariate analysis techniques to evaluate individual players. Principal component analysis (PCA) is one of the most usable multivariate analysis applied in football to select KPI (Gómez, 2012; Moura, 2013; Lago-Peñas, 2017). PCA is one of the ways to efficiently summarize multidimensional data that correlates between variables into low-level data. This PCA was raised by Pearson (1901) as a matter of geometric optimization to find the plane best suited for the concept of the least -squares method by which the scattered points in the p-dimensional space are best suited. Hotelling (1933) then obtained lower-level, independent factors that determine the variation of the original variables of p numbers to analyze the correlation between the variables and thus, called this component 'main component analysis' where the analysis of the components are chosen to sequentially maximize the contribution of each component to the total variation of the original variables (Jolliffe, 2002). Gómez (2012) examined the game location and outcome using PCA and suggested that home and winning team had better indicator values. PCA was also used to distinguish component indicators to distinguish winning teams in 2006 World cup (Moura, 2013), and to correlate which factors can explain possession in professional soccer (Lago-Peñas, 2018).

Using PCA, exploratory factor analysis provided us with factor loading values of each indicator for the factors. A factor loading shows the correlation between the indicator and the factor. Therefore, the higher the factor loading, the better the factor explains the corresponding indicator (Jung, 2018). This analytic method has been used extensively in the studies of economics and sociology to create an index to evaluate the most influential indicators. (Nicoletti, 2000; Nardo, 2005). For example, by using these methods, we can figure out which indicators are priority for each positions of players.

Despite such efforts for a performance evaluation in football, studies have been examined and focused on specific positions using the same indicators with different weight. Thus, focusing on different primary indicators for different positions using multivariate analytic methods should be our concern. Many previous studies categorized players according to positions, but most divided them into forwards, mid-fielders and defenders. However, a player's role in the field differs according to the place in which he plays. Therefore, the purpose of this study is to investigate the primary indicators using PCA with an index for evaluating a defender's technical performance and spot the distinguishing features of central and wide defenders.

Methods

Participants

Data of professional football players who played as defenders in English Premier League, German Bundesliga or Spanish La Liga (three of the top five highest Association Club Coefficients from UEFA for 2017/2018 season) during the 2017/2018 season were sampled (UEFA, 2018). English Premier League 2017/2018 was the latest season when data acquisition was available. As a result, a total of 472 players, 233 central defenders from German Bundesliga (n = 70), Spanish La Liga (n = 80), English Premier League (n = 83) and 233 wide defenders from German Bundesliga (n = 66), Spanish La Liga (n = 92), English Premier League (n = 81) were selected. The mean age for the players was 26.4 years (German Bundesliga = 25, Spanish La Liga = 26.8, and English Premier League = 27.2). We divided the subjects into central defenders and wide defenders, as the two differ in their roles on the field and thus should be differently evaluated (Bush et al., 2015).

Variables

A statistical website "Squawka" was used to examine the players' performance and to collect the profiles of each player, which draws its raw feed licensed from its data provider Opta. The collected football match statistics by OPTA's tracking system has been evaluated as reliable sources (Liu, 2013). To attain the potential indicators for central and wide defenders, we sorted out 23 out of 48 indicators provided. Eight goalkeeper-related indicators were excluded as the study focused on field players. "Goals Conceded" was not categorized as goalkeeper statistics but was excluded as it showed 0 for all field players. The other 16 indicators were left out as they showed the means to actions, rather than the result itself. For instance, "Goals – left footed" and "Goals – right footed" were excluded as they overlapped with "Goals Scored". Indicators definitions can be found here: (https://www.optasports.com/news/optas-event-definitions/).

Methodology

In the initial raw data collected, a simple conversion of all players' indicators to 90minutes caused abnormal numbers like 3 minutes players' 5 shots into 150 shots for 90 minutes which is way above the average. The limitation of this inappropriate conversion was solved with the equation created by James et al. (2005).

$$\text{Transformation} = \text{F}\ \left(\frac{\sqrt{90}}{n}\right)\left(\left(\log\ \frac{1090}{n}\right)+1\right)$$

Where F is the frequency of each indicator and n is the number of actual time players played.

And the PCA was performed was performed with every match indicator to extract primary indicators of defenders' performance. Varimax rotation method was also used to sort out the structure of components. The result of the Kaiser-Meyer-Olkin measure confirms the suitability of data for PCA and the significance level from Bartlett's test was 0.0001 ($p < 0.05$). After confirming the suitability of our data, the screen test depicting the eigenvalues was conducted to check the appropriate number of factors. The number of eigenvalues bigger than 1 became an appropriate number of factors for PCA.

We selected the indicators with the highest factor loading values for each factor, after which the values are squared to get rid of negatives. The sum of the squared factor loadings within a specific factor became the explained variance of that factor. Moreover, the initial weight of an indicator, representing the portion that the indicator takes in the factor, is drawn out by dividing the squared factor loading of the indicator by the explained variance of the factor. The final weight of an indicator is calculated by multiplying this initial weight with the percentage of the variance of the factor. The percentage of the variance of the factor demonstrates the portion that the factor takes within the total sum of the explained variance of all the factors. In short, the squared factor loading of an indicator was divided by the total variance of factors to provide the final weight (Nardo, 2005).

Statistics

All the statistical analyses were conducted using SPSS for Windows, version 25.0 (IBN, Inc.).

Table 1. *Eigenvalues for components and total variance explained.*

	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.74	20.63	20.63	4.74	20.63	20.63	4.32	18.79	18.79
2	2.84	12.36	33.00	2.84	12.36	33.00	2.64	11.49	30.28
3	2.06	8.99	42.00	2.06	8.99	42.00	2.23	9.71	40.00
4	1.75	7.61	49.61	1.75	7.61	49.61	1.77	7.71	47.71
5	1.57	6.83	56.45	1.57	6.83	56.45	1.68	7.34	55.05
6	1.46	6.36	62.81	1.46	6.36	62.81	1.53	6.68	61.73
7	1.25	5.46	68.28	1.25	5.46	68.28	1.50	6.54	68.28
8	1.07	4.68	72.96						
9	0.92	4.01	76.98						
10	0.88	3.85	80.84						
11	0.73	3.19	84.03						
12	0.65	2.83	86.87						
13	0.54	2.35	89.22						
14	0.50	2.18	91.41						
15	0.42	1.85	93.27						
16	0.36	1.59	94.86						
17	0.33	1.46	96.32						
18	0.31	1.38	97.70						
19	0.28	1.24	98.94						
20	0.23	1.02	99.97						
21	0.00	0.02	99.99						
22	0.00	0.00	100.00						
23	0.000	0.00	100.00						

Results

Central Defenders

The result of the KMO measure over 0.5 confirms the suitability of data for PCA. The result of the measure was 0.579, confirming the suitability of the 233 central defenders' data, which was supported by the significance level from Bartlett's test of 0.0001 ($p < 0.05$). The eigenvalues of 23 indicators of central defenders showed that seven factors can be the appropriate number of factors and were used for this study, explaining 68.28% of the total variance (see Table 1).

The result of the PCA shows the factor loading values of each indicator to the factors (see Table 2). The factor in which the indicator has the highest factor loading value is considered the factor that indicator has the strongest correlation with. The squared factor loading values of each indicator were added to show the explained variance of each factor. The percentage of variance, representing the part that a specific factor takes within all the factors, was drawn out by dividing the factor's explained variance into the total variance of all factors. As shown in Table 1, Factors 1 to 7 had a portion of 0.33, 0.18, 0.15, 0.10, 0.11, 0.10, and 0.09, respectively, the values rounded to the second decimal place.

The initial weight, representing the portion of the indicator within its corresponding factor, was shown by dividing the indicator's squared factor loading with the explained variance of the factor (see Table 2). Multiplying this value with the percentage of the variance of its factor drew out the final weight of each indicator. The indicators with the highest weight were "Tackles Lost" and "Defensive Errors", whereas "Red Cards," "Assists" turned out to be lowest (see Table 3).

Table 2. *Result of the principal component analysis for central defenders with 23 indicators.*

	Factor						
Variables	1	2	3	4	5	6	7
Key Passes	0.169	0.158	0.903	0.085	0.097	0.055	- 0.026
Successful Passes	0.975	- 0.030	0.112	- 0.066	0.031	0.028	- 0.015
Total Passes	0.969	0.023	0.144	- 0.023	0.039	0.041	- 0.022
Yellow Cards	- 0.149	0.348	0.091	- 0.087	0.192	0.129	0.483
Chances Created	0.174	0.139	0.946	0.030	0.106	0.013	- 0.029
Assists	0.061	- 0.045	0.431	- 0.204	0.059	- 0.164	- 0.025
Fouls Committed	- 0.048	0.740	0.064	- 0.151	0.333	0.048	0.160
Tackles Lost	- 0.061	0.849	0.075	0.026	- 0.027	0.036	0.093
Total Back Passes	0.839	0.154	0.072	- 0.163	0.119	- 0.022	- 0.150
Pass Completion	0.767	- 0.015	- 0.030	- 0.011	0.037	- 0.037	0.300
Interceptions	0.128	0.670	- 0.049	0.412	0.062	- 0.061	- 0.146
Total Forward Passes	0.930	- 0.037	0.163	0.040	- 0.002	0.064	0.035
Aerial Duels Won	0.218	- 0.100	0.099	- 0.126	0.136	- 0.261	0.665
Tackles Won	0.134	0.758	0.089	- 0.091	- 0.165	- 0.153	- 0.173
Clearances	- 0.245	- 0.091	0.100	0.746	-0.029	- 0.013	0.277
Fouls Suffered	0.003	0.305	0.083	0.044	0.512	- 0.060	0.038
Total Shots	0.158	- 0.135	0.223	- 0.115	0.623	0.055	0.223
Successful Take-On	0.024	- 0.025	- 0.235	0.185	- 0.085	0.139	0.663
Blocks	- 0.015	0.023	- 0.112	0.825	- 0.048	- 0.036	- 0.126
Goals Scored	0.024	- 0.033	0.030	- 0.019	0.800	- 0.058	- 0.036
Red Cards	0.103	0.145	- 0.310	0.370	0.382	0.201	- 0.185
Errors leading to Goal	0.011	- 0.038	- 0.026	- 0.159	- 0.041	0.796	- 0.059
Defensive Errors	0.060	- 0.044	- 0.058	0.134	0.009	0.824	0.079

Table 3. *Initial and final weights of each individual indicator.*

Variable	Initial Weight	Final Weight
Successful Take-On	0.3145	0.1041
Total Shots	0.5174	0.0970
Errors leading to Goal	0.4825	0.0905
Defensive Errors	0.4717	0.0885
Interceptions	0.5499	0.0853
Fouls Committed	0.2389	0.0791
Red Cards	0.1956	0.0648
Chances Created	0.3938	0.0610
Total Back Passes	0.1739	0.0576
Tackles Lost	0.45	0.0528
Goals Scored	0.2704	0.0507
Yellow Cards	0.1453	0.0481
Pass Completion	0.4454	0.0450
Key Passes	0.4302	0.0435
Total Forward Passes	0.3965	0.0401
Aerial Duels Won	0.2096	0.0393
Assists	0.2136	0.0331
Blocks	0.2508	0.0294
Fouls Suffered	0.1825	0.0283
Tackles Won	0.2349	0.0252
Successful Passes	0.2321	0.0249
Total Passes	0.098	0.0183
Clearances	0.1015	0.0102

Wide defenders

The results of the KMO measure and Bartlett's test for significance level for wide defenders were 0.634 and 0.001 respectively ($p < 0.05$), verifying the suitability of the data for PCA. The eigenvalues showed that appropriate number of factors was seven. The PCA was done with seven factors, with a cumulative variance of 71.70% (see Table 4).

The result of the PCA for wide defenders was also explained by seven factors (see Table 5). Using the same approach of central defenders, the explained variance of each of the seven factors of wide defender's performance was calculated by adding the squared factor loading values of the indicators. The explained variance was divided by total variance to represent the percentage of the variance of each factor. Factors 1 to 7 had a portion of 0.30, 0.20, 0.19, 0.12, 0.10, 0.06, and 0.05, respectively, the values rounded to the second decimal place.

Table 4. *Eigenvalues for components and total variance explained.*

	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.34	23.23	23.23	5.34	23.23	23.23	4.30	18.71	18.71
2	3.50	15.23	38.46	3.50	15.23	38.46	3.15	13.71	32.43
3	2.48	10.81	49.28	2.48	10.81	49.28	2.93	12.76	45.19
4	1.62	7.04	56.33	1.62	7.04	56.33	1.84	8.02	53.22
5	1.44	6.26	62.59	1.44	6.26	62.59	1.68	7.30	60.53
6	1.07	4.69	67.28	1.07	4.69	67.28	1.34	5.85	66.38
7	1.01	4.41	71.70	1.01	4.41	71.70	1.22	5.31	71.70
8	0.96	4.21	75.91						
9	0.83	3.64	79.55						
10	0.74	3.23	82.79						
11	0.69	3.02	85.82						
12	0.63	2.73	88.55						
13	0.53	2.31	90.87						
14	0.48	2.11	92.99						
15	0.37	1.63	94.63						
16	0.36	1.59	96.22						
17	0.28	1.25	97.47						
18	0.22	0.98	98.45						
19	0.19	0.85	99.31						
20	0.15	0.67	99.98						
21	0.00	0.01	99.99						
22	0.00	0.00	100.00						
23	0.00	0.00	100.00						

Table 5. *Result of the principal component analysis for wide defenders with 23 indicators.*

Variables	Factor 1	2	3	4	5	6	7
Key Passes	0.123	- 0.035	0.882	0.086	0.143	- 0.132	0.180
Successful Passes	0.975	0.035	0.140	0.005	0.123	- 0.001	0.045
Total Passes	0.949	0.098	0.137	0.049	0.145	0.009	0.093
Yellow Cards	- 0.173	0.790	- 0.013	0.011	- 0.044	0.184	- 0.184
Chances Created	0.165	- 0.044	0.917	0.049	0.119	- 0.105	0.129
Assists	0.293	- 0.065	0.555	- 0.158	- 0.064	0.086	- 0.193
Fouls Committed	- 0.057	0.881	- 0.009	- 0.026	- 0.019	- 0.040	- 0.064
Tackles Lost	0.085	0.742	- 0.111	- 0.024	0.086	0.112	0.230
Total Back Passes	0.907	0.011	0.239	- 0.045	0.157	- 0.050	- 0.058
Pass Completion	0.780	- 0.188	0.115	- 0.107	- 0.008	- 0.046	- 0.097
Interceptions	0.031	0.539	- 0.268	0.120	0.171	- 0.075	0.468
Total Forward Passes	0.804	0.180	- 0.008	0.146	0.103	0.077	0.250
Aerial Duels Won	0.011	0.182	- 0.330	- 0.034	0.282	0.415	- 0.368
Tackles Won	0.212	0.671	0.019	0.122	- 0.106	- 0.045	0.264
Clearances	- 0.226	0.117	- 0.529	0.249	- 0.039	0.401	0.094
Fouls Suffered	0.087	0.530	0.180	- 0.046	- 0.142	- 0.479	- 0.015
Total Shots	0.138	0.058	0.280	0.062	0.833	- 0.134	0.002
Successful Take-On	0.074	0.062	- 0.006	0.155	- 0.240	0.786	0.104
Blocks	- 0.011	- 0.062	- 0.532	0.235	- 0.138	- 0.038	0.042
Goals Scored	0.270	- 0.134	0.072	- 0.067	0.805	- 0.018	0.018
Red Cards	0.075	0.111	0.074	- 0.094	- 0.004	0.100	0.713
Errors leading to Goal	0.003	0.082	- 0.104	0.902	- 0.027	0.008	- 0.074
Defensive Errors	0.020	- 0.030	- 0.104	0.876	0.024	0.184	0.005
Key Passes	0.123	- 0.035	0.882	0.086	0.143	- 0.132	0.180

Table 6. *Initial and final weights of each individual indicator*

Variable	Initial Weight	Final Weight
Successful Take-On	0.7816	0.1519
Total Shots	0.5167	0.1081
Errors leading to Goal	0.5144	0.1076
Defensive Errors	0.4855	0.1016
Interceptions	0.3008	0.0922
Fouls Committed	0.2895	0.0887
Red Cards	0.6991	0.0862
Chances Created	0.3377	0.0706
Total Back Passes	0.2092	0.0641
Tackles Lost	0.205	0.0628
Goals Scored	0.4832	0.0596
Yellow Cards	0.2326	0.0486
Pass Completion	0.1548	0.0474
Key Passes	0.3122	0.0385
Total Forward Passes	0.1645	0.0319
Aerial Duels Won	0.2183	0.0269
Assists	0.1237	0.0258
Blocks	0.1137	0.0221
Fouls Suffered	0.1047	0.0203
Tackles Won	0.168	0.0175
Successful Passes	0.2419	0.0149
Total Passes	0.2293	0.0141
Clearances	0.1125	0.0117

For wide defenders, “Successful Take-on” and “Total Shots” turned out to have the biggest weight, followed by “Clearances” and “Total Passes” had the least importance.

Although similar in general, the results of weights of some indicators distinguished the features of central and wide defenders. “Defensive Errors” and “Errors Leading to Goal” were in top 5 indicators for central defenders as well as for wide defenders (see table 6).

Discussion

The purpose of this investigation is to identify and understand the primary indicators for evaluating the performance of central and wide defenders in football games. Using 23 indicators and the method of principal component analysis, the major findings of this study are 1) “Tackles Lost” and “Defensive Errors” were the most important indicators for central defenders, and

“Successful Take-on” and “Total Shots” for wide defenders and therefore 2) the two positions should be evaluated on different standards. And these findings can be applied to real football field like scouting future players with primary indicators for central and wide defenders.

Following the previous studies, this study used statistical method to objectively represent individual performance in team sports. Instead of focusing on the overall player’s physical area, this study focused on technical statistical indicators for a specific position. While this study showed that “Tackles Lost” and “Defensive Errors” had the biggest weight for central defenders and “Successful Take-on” and “Total Shots” for wide defenders, Hong (2017) pointed out that “Aerial Duels Won,” “Interceptions” and “Tackles” were the most important technical factors for defenders. This difference might be because Hong selected 12 indicators in total using the Delphi method and did not divide the defenders depending on their place on the field. By using different factors, McHale, Scarf and Folker (2012) developed a performance rating system for the English Premier League. Herein, match outcome was used as a primary factor and five other subindices such as appearance and goal-scoring were used to compose a final index. In terms of the technical field, it is possible that the results would be different should other statistical indicators are used. Mackenzie and Cushion (2013) also pointed out that many studies on performance evaluation using statistical indicators are conducted on the availability of the data. As different indicators might lead to different result even with same scientific method, scientific studies on the usage of indicators for the player evaluation would contribute to more acceptable results. In this study, a multivariate analysis method is conducted with PCA to create a new index which was confirmed in literature from other fields (Nardo, 2005). As many statistical methods have been used in sport (Perl, 2018), more new approaches should be considered for further studies.

The results based on defenders’ technical indicators showed that the indicators have a different weight according to the position in which they play. Wide defenders’ higher weight of “Successful Take-on” and “Total shots” than central defenders confirms that wide defenders need greater technical skills for competitive situations with pressure (Schuth, 2016). On the other hand, central defenders showed greater weight of defense actions such as “Aerial Duels Won,” “Blocks,” “Tackles Won,” “Tackle Lost” and “Clearances.” As wide defenders cover more total distances and area than central defenders to deliver balls to the final third (Bush, 2015), greater defense actions for central may be needed. Further study should be done with considering the contextual situation and position interchanges to examine more detail differences according to positions. We expect there would be difference between defenders and forwards, and even among forwards depending on their place on the field. Further studies on forwards using similar approaches would contribute to a better understanding of the performance evaluation of professional football players.

As there is no definite standard for the main players in teams, we understand that there could be other opinions on enough playing time for main players. For example, English Premier League does not provide league champion medals to players who made less than 5 appearances during the season. The result shown in Table 5 was based on defenders who played at least 1/3 of the playing time during the entire season. As the season goes, a player may take a break due to the team’s rotation system or due to injuries. We decided that 1/3 would be the right playing time to consider these aspects and to include as many players as possible for analysis. A definite, universal standard on playing time would make the system more acceptable.

Level of the team for which the player plays should also be taken into account when evaluating his performance. As contextual variables in football can affect the styles of a player in football, contextual variables must be considered when analyzing performance in football (Fernandez-Navarro, 2018).

When introducing an index system for players in the English Premier League, McHale, Scarf and Folker (2012) noted that the player's performance depends on the situation in which he faces during the games. A defender of a weaker team would spend more time defending his area than that of a dominant team. On the other hand, a defender of a dominant team, would have fewer opportunities to take defensive actions as his team would focus on attacking rather than defending. The same applies to forwards. Further studies on including the level of the teams for individual technical performance would contribute to developing a more elaborate index.

Evaluation on a technical level is only a part of a player's performance. A player's performance also consists of his physical level. A wide range of studies on professional player's physical levels is being done and implied on the field. Further studies on such both physical and technical field would make the performance evaluation more detailed.

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