Original Article

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A multi-criteria system for performance assessment and support decision-making based on the example of Premier League top football strikers

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Abstract: The effective management of sports teams plays a pivotal role in achieving substantial success. In this pursuit, an increasing number of teams are resorting to information systems to enhance decision-making processes. These systems ensure the implementation of well-informed decisions, thereby contributing additional insights into training management. Through their assistance, it becomes feasible to optimize both player potential and overall team performance. In this paper, we propose a decision system rooted in the Multi-Criteria Decision Analysis (MCDA) approach, complemented by sensitivity analysis, to assess the performance of soccer players. The evaluation focused on football players in the forward position in the Premier League during the seasons 2015-2021. Subsequently, a sensitivity analysis of the results was conducted to delineate key elements in the game that significantly influence performance quality. Based on these findings, adjustments to a player's training plan can be made, targeting specific aspects of the game to enhance the player's potential. The study's results underscore that, with appropriate enhancements to players' performance, they can achieve markedly superior ratings compared to their counterparts.

Keywords: Soccer player performance; Sensitivity analysis; Decision-making

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INTRODUCTION

Football stands out as one of the most widely practiced sports globally [1]. The matches draw a vast number of fans who ardently follow the games of their favorite clubs [2]. Moreover, it serves as a magnet for young individuals aspiring to train in football clubs, nurturing dreams of a future career at the highest echelons of the sport. With an escalating level of professionalism permeating the football training management process, there is a surge in the adoption of new technologies and solutions aimed at aiding both players and coaches [3]. These technologies facilitate the identification of areas within team and club performance that, if enhanced, can significantly contribute to progress and improved player performance [4]. The advantages offered by these systems have led to an increasing interest from teams in adopting such technologies.

Information systems dedicated specifically to sports management and football coaching applications are gaining traction [5]. These systems are tailored for various facets of football, including club management [6], player selection [7], marketing [8], and player performance analysis [9]. The insights provided by these systems enrich the player development process with well-informed and computationally supported training measures, presenting an intriguing option to elevate club processes and enhance player quality, thereby improving overall club performance. Yang's study emphasizes the facilitative role of information systems in club development, spanning business processes, operations, internal communication, and decision-making [10]. Similarly, Li and Zhang's research focuses on a system designed to support learning and skill development in football, demonstrating increased player enthusiasm and improved team performance [11]. Blobel and Lames developed a Club Management Information System (CMIS) addressing performance analysis and player health to aid day-to-day decision-making [12]. Górecka tackled the sponsorship selection problem using a multi-criteria approach, considering different weights to model decision criteria relevance [13]. Sałabun et al. evaluated football players' performance using the Characteristic Objects Method (COMET) and integrated fuzzy logic in sports evaluation [14].

Many dedicated systems supporting club operations rely on decision support methods [15]. Given the myriad challenges in daily football club management, rational and optimal decision-making is imperative to maximize the club's potential [16]. Multi-Criteria Decision Analysis methods, a core technique in these support systems, can be adapted to various areas of club management by tailoring criteria to specific problems. Gökgöz and Yalçın employed a combination of Weighted Aggregated Sum Product Assessment (WASPAS) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods to analyze World Cup team performances [18]. Khatrouch et al. used the Analytical Hierarchy Process (AHP) to establish individual decision-maker preferences and assess team performance based on multiple criteria [19]. Qader et al. designed a player selection system based on fitness tests, analyzing results using the TOPSIS method [20]. The growing popularity of dedicated decision support systems in football club management suggests that such solutions enhance team efficiency.

Recently developed information systems dedicated to supporting team management in football are gaining popularity for their usability and high practical potential [21]. Proposing innovative ways to support decision-making becomes crucial as it can lead to more substantial improvements in training resources. The increasing trend in constructing decision support systems for football club management involves techniques such as player assessments based on photo and video analysis, statistical analysis, predictive algorithms, process automation, and machine learning mechanisms [23-25]. This diversity allows the creation of holistic systems that consider various aspects of sports club management, supporting decisions at different levels, from individual player development to managing the entire team and young academy prospects [26-28]. A well-structured decision support system not only facilitates daily work with players but also boosts operational efficiency.

Given the persistent demand for dedicated decision support systems in football club management, proposing novel solutions is vital for team development and improving game efficiency and effectiveness. In this paper, we introduce a decision support system based on a multi-criteria decision analysis approach, coupled with sensitivity analysis of the results. The system, founded on the TOPSIS method, assesses the quality of players' games and utilizes sensitivity analysis to identify potential directions for player development, contributing to enhanced performance relative to other players. The model's performance was validated using data from the 2015-2021 Premier League seasons, focusing on the assessment and analysis of areas for improving performance, specifically for strikers. The aim is to propose a model that identifies directions for footballers' development, leading to significant improvements in the quality of their performances.

This research aims to present a decision-making model for assessing performance quality throughout a football season. Applying the chosen approach to conduct sensitivity analysis intends to highlight areas in a player's game that can enhance performance relative to others. Quantifying the volume of improvement in performances against specific criteria in a sensitivity analysis provides a quantitative measure of how changes in selected statistics affect a footballer's performance rating. This knowledge allows identification of the most significant area of the game influencing a player's performance quality, enabling targeted training to develop specific aspects of the game.

METHODOLOGY

The TOPSIS method

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method was developed by Chen and Hwang [29]. The technique determines each decision variant's distance to the Ideal Solution (IS). Based on IS, the preference for alternatives is calculated [30]. To present the formal notation of the method, its' main steps should be introduced [31].

Step 1. Determination of the decision matrix in the multi-criteria problem:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix}$$

Step 2. Normalization of the defined decision matrix X:

$$\text{Profit: } r_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \qquad \text{Cost: } r_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})}$$

$$i = 1, \ldots, m \qquad j = 1, \ldots, n$$

Step 3. Calculation of a weighted normalized decision matrix:

$$v_{ij} = w_i \cdot r_{ij}, \qquad i = 1, \ldots, m \quad j = 1, \ldots, n$$

Step 4. Identification of the Positive and Negative Ideal Solutions for a defined decision-making problem:

$$A_i^* = \{v_1^*, \dots, v_n^*\} = \left\{\left(\max_j v_{ij} \mid i \in I^P\right), \left(\min_j v_{ij} \mid i \in I^C\right)\right\}$$
$$A_i^- = \{v_1^-, \dots, v_n^-\} = \left\{\left(\min_j v_{ij} \mid i \in I^P\right), \left(\max_j v_{ij} \mid i \in I^C\right)\right\}$$

where I^P stands for profit type criteria and I^C for cost type.

Step 5. Calculation of the Positive and Negative Distances using the n-dimensional Euclidean distance:

$$D_i^* = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^*\right)^2},$$
$$i = 1, \dots, m$$

$$D_i^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^-\right)^2},$$
$$i = 1, \dots, m$$

Step 6. Calculation of the relative closeness to the Ideal Solution:

$$C_i^* = \frac{D_i^-}{\left(D_i^* + D_i^-\right)},$$

$$i = 1, \dots, m$$

Equal weighting methods

The equal weights technique provides the same weight value for each criterion [32]. It translates into having equal importance of all criteria in the decision problem. The weights can be calculated as follows:

$$w_j = \frac{1}{n} j \in \{1,2, \dots, n\}$$

Correlation coefficients

The Weighted Spearman correlation coefficient allows for comparing two ranking vectors [33]. The coefficient uses the weights for determining the importance of differences occurring in the ranking's coherence [34]. The correlation can be calculated with the following formula:

$$r_w = 1 - \frac{6 \cdot \sum (x_i - y_i)^2 \left((n - x_i + 1) + (n - y_i + 1)\right)}{n \cdot (n^3 + n^2 - n - 1)}$$

where x_i means position in the reference ranking, y_i is the position in the second ranking and N is the number of ranked elements.

The WS rank similarity coefficient is based on assigning a greater significance to the elements in the top part of the ranking [35]. The differences in higher positions will cause a lower similarity value than the same differences at the bottom of the ranking [36]. The calculation formula for the WS similarity coefficient is presented as:

$$WS = 1 - \sum\left(2^{-x_i} \frac{|x_i - y_i|}{\max\{|x_i - 1|, |x_i - N|\}}\right)$$

where x_i means position in the reference ranking, y_i is the position in the second ranking and N is a number of ranked elements.

Data Preparation

In pursuit of developing a model to support the identification of areas requiring special attention in training and matches played, the TOPSIS method was employed. An evaluation of players' performance quality in Premier League matches spanning the seasons from 2015 to 2021 was conducted based on a defined set of criteria. The evaluation specifically focused on forwards who participated in matches during at least five of the six analyzed seasons.

The study incorporated a sensitivity analysis approach, exploring areas in players' games that, if improved, could potentially enhance the quality of their performances. A modified sensitivity analysis technique, as presented by Wolters and Mareschal [37], involved adjusting the decision matrix to ensure promotion to a specific alternative in the ranking. For profit-type criteria, changes were limited to a tenfold multiplication of the initial value in the decision matrix. For instance, if the initial value for A_1 and C_1 was 5, the maximum value considered in the sensitivity analysis was 50. Conversely, for cost-type criteria, changes were restricted to zero.

With established bounds for changes in the decision matrix, players' performance data were analyzed for each season from 2015/2016 to 2020/2021. Modifications to the initial decision matrix for a single criterion and single alternative were employed to illustrate how enhancing performance in a given criterion could impact the overall score in the assessment. As criteria-specific bounds were set, the goal was to seek maximal potential ranking promotions with the smallest possible performance improvement, ensuring the highest possible rank position. This approach aims to quantitatively indicate the scale of needed performance improvement in a specific area of the game to enhance the overall assessment relative to other analyzed forwards.

Study Case

The dataset for the multi-criteria decision analysis was sourced from statistics available on the website WhoScored.com [38]. The players' dataset is accessible in the open repository [39]. During preprocessing, the analyzed set was narrowed down to players occupying the striker position over the 2015-2021 seasons, focusing on those participating in the Premier League. Another condition stipulated that players must have played at least five of the six seasons under analysis. This criterion aimed to assess players' performances in consistent playing conditions over the studied years, evaluating their successive performances at their respective clubs. Ultimately, the set of players meeting these requirements consisted of 26 footballers. Figure 1 visually depicts each player's participation in each season, with the white box indicating non-participation in the Premier League during a given season.

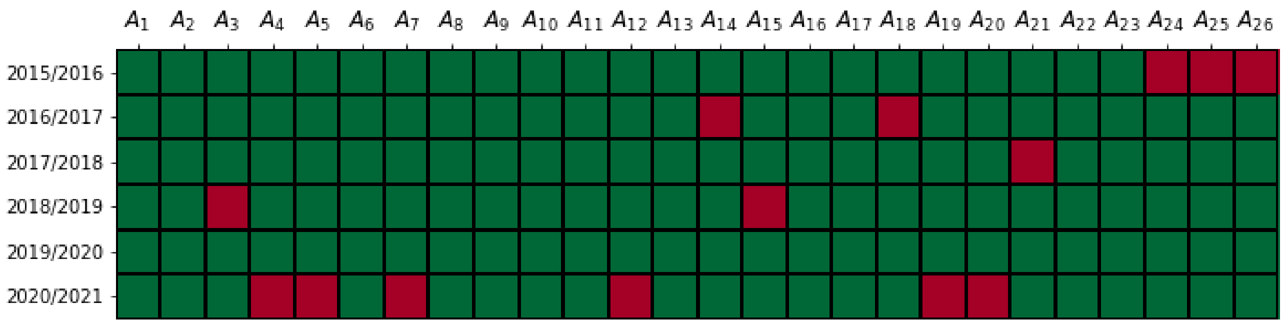

Figure 1. Visualisation of player participation in each season, where a red frame indicates no participation in the Premier League in a given season. Green frame - the player took an active part in a given season. Symbols A1 to A26 represent the 26 players who qualified for the study.

Table 1. Criteria identified for the problem of offensive football players' performance evaluation determined based on the data available and explained in https://www.whoscored.com/Statistics

Evaluation area	C_i	Full name	Type
Overall skills	C_1	Pass success percentage	Profit
	C_2	Key passes per game	Profit
	C_3	Total assists	Profit
Offensive skills	C_4	Shots per game	Profit
	C_5	Fouled past per game	Cost
	C_6	Bad control per game	Cost
	C_7	Total goals	Profit
	C_8	Offsides per game	Cost
	C_9	Dribbles per game	Profit
	C_{10}	Dispossessed per game	Profit
	C_{11}	Shots to Goal ratio	Cost
	C_{12}	Goals per minute	Profit
	C_{13}	Assists per minute	Profit

Based on the available data, 13 criteria were identified to assess players' performance. Two evaluation areas were defined. The overall skills area includes 3 criteria: the percentage of successful passes (C_1), mean value key passes per game (C_2), and number of total assists (C_3). The second evaluation area concerns the offensive skills with 10 criteria. The factors describing the players' performance that were taken into consideration were: mean value of shots per game (C_4), mean value of fouled past per game (C_5), mean value of bad ball control per game (C_6), number of total goals (C_7), mean value of offsides per game (C_8), mean value of dribbles per game (C_9), mean value of ball dispossession per game (C_{10}), shots-to-goal ratio (C_{11}), scored goals per minute of play (C_{12}), and assists per minute of play (C_{13}). First ten criteria (C_1 - C_{10}) were strictly derived from the available dataset [37], where the criteria C_{11} - C_{13} were calculated from the available data. The criteria selection process was based on the importance of each of the presented factors in the game of the forwards, making their performance effective and efficient. The set of criteria considered in the study was presented in Table 1, where the evaluation area, a symbol representing a particular criterion with its' full name and type of criterion required to be established for the multi-criteria assessment purposes, were included.

Table 2. Part of the decision matrix defined for the problem of offensive football players' performance evaluation (Season 2020/2021) (Ai -players Ci - parameters)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	69.9	1.4	14	3.9	1.7	1.8	23	0.4	0.5	1.5	5.94	0.0074	0.0045
A_2	81.7	3.2	12	3.2	1.2	1.8	6	0.0	1.4	1.3	12.27	0.0030	0.0060
A_3	78.7	1.7	7	2.7	2.2	2.9	11	0.9	0.6	1.7	7.61	0.0039	0.0025
A_4	83.4	2.0	10	1.8	1.5	1.6	17	0.4	1.5	1.4	3.81	0.0054	0.0032
A_5	86.2	1.3	7	2.3	1.3	2.0	10	0.3	0.2	2.7	6.44	0.0039	0.0027
A_6	68.2	1.0	5	2.4	1.5	3.0	10	0.6	0.2	1.9	5.76	0.0050	0.0025
A_7	82.1	1.2	9	2.1	1.1	2.1	11	0.7	0.5	1.4	6.30	0.0037	0.0031
A_8	80.7	1.2	7	2.3	0.4	2.2	9	0.1	0.7	1.3	8.43	0.0031	0.0024
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
A_{19}	74.4	0.8	3	1.4	1.4	2.7	3	0.4	1.0	1.3	9.33	0.0018	0.0018
A_{20}	76.8	1.0	3	1.6	0.5	1.4	2	0.1	0.6	1.3	13.60	0.0011	0.0017

Parameters A1 to A20 represent subsequent players. Parameters: (C1 Pass success percentage, C2 Key passes per game, C3 Total assists, C4 Shots per game, C5 Fouled past per game, C6 Bad control per game, C7 Total goals, C8 Offsides per game, C9 Dribbles per game, C10 Dispossessed per game, C11 Shots to Goal ratio, C12 Goals per minute, C13 Assists per minute)

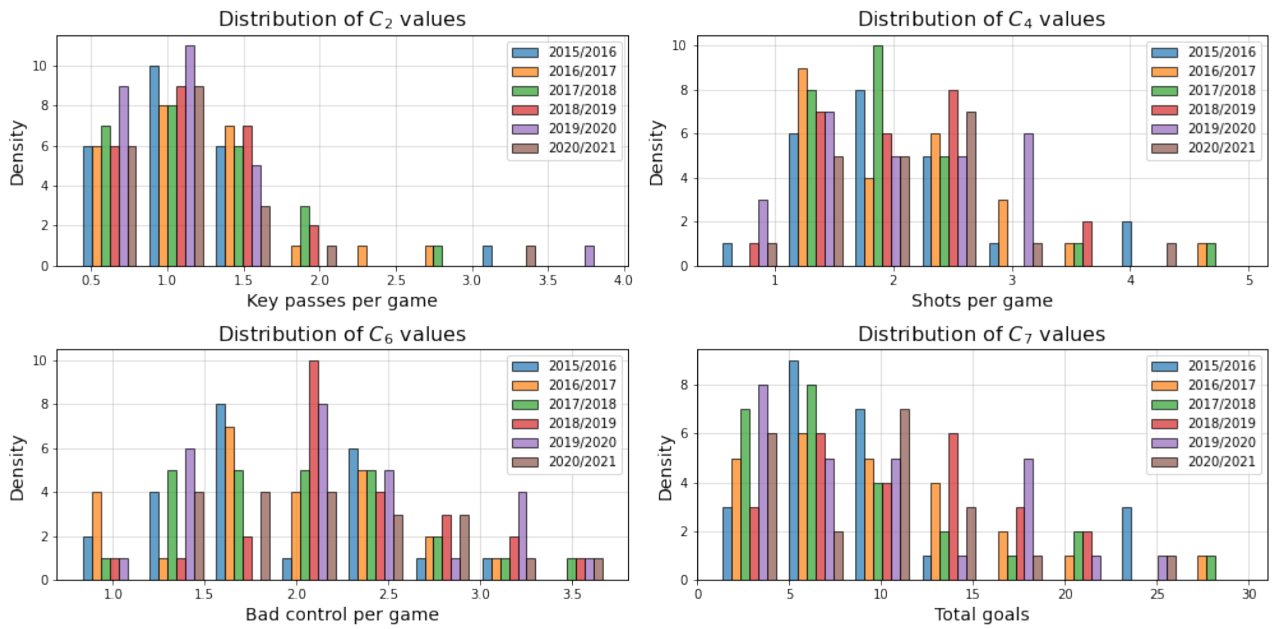

Figure 2. Distribution of values for C_2 (Key passes per game), C_4 (mean values of shots per game), C_6 (mean bad ball controls per game) and C_7 (number of total goals) criteria during the analysed seasons.

The data based on which the evaluations were made were stored in the decision matrix, which contained the specific values characteristic for specific alternatives under given criteria. The decision matrices used in the assessment process were established separately for each season, including forwards engaged in the games. To this end, 6 decision matrices were identified. The part of the decision matrix determined for data obtained for the 2020/2021 season was presented in Table 2. Moreover, all complete decision matrices used in the study were presented in the Appendix section (Tables 5 – 10). Since six players were not participating in matches in season 2020/2021, only 20 players were evaluated this season. On the other hand, from Figure 1, it can be seen that the season 2019/2020 was the only season in which every considered forward was actively playing games during the season.

Due to the different course of the season and individual matches throughout the seasons considered, it was worth presenting the distribution of the data regarding selected criteria. The visualization of the data distribution is presented in Figure 2, where histograms representing the distribution of the mean value of key passes per game (C_2), mean values of shots per game (C_4), mean bad ball controls per game (C_6), and number of total goals (C_7) are presented.

It can be seen that the data distribution differs from one criterion to another, with a similar effect for seasons comparison. For the criterion C_2 corresponding to the mean value of key passes per game, it should be noted that most of the values are placed within the range of 0.5 to 1.5 passes. Moreover, it can be seen that only 5 forwards were able to maintain mean values of key passes per game during the six analyzed seasons. Comparing the distribution of values corresponding to the players' performance regarding the mean values of shots per game (C_4), it can be seen that most players keep the number of shots in a single football match between 1 to 3 shots. However, what should be noted is that in season 2019/2020, more players were able to maintain more than 3 shots in a single game during the season, which stands out from the rest of the analyzed seasons' results. For the mean values of bad ball control per game (C_6), it can be seen that most of the values were placed in the middle of the range. Furthermore, it is worth pointing out that the discrepancies between compared distributions were visible depending on the analyzed season. For example, data for the season 2019/2020 was more focused on the right range of values, while for the season 2015/2016, the data were distributed mainly in the left range of values. The last presented data distribution was visualized for the criterion C_7, representing the number of total goals scored in the season by forwards. It can be noted that most of the players score from 3 to 10 goals per season. However, some forwards significantly exceed this range and, in some seasons, achieve a total number of goals greater than 25.

To present the mean values of each criterion taken into account while assessing players regarding their performance throughout the season, Table 3 was included. From the mean values presented, it can be seen how the seasons differ from each other in general. It can be seen that seasons 2016/2017 and 2018/2019 resulted in scoring the highest mean value of goals (C_7) in seasons by forwards. On the other hand, in season 2020/2021, the mean amount of scored goals in all games was the lowest. Another interesting fact coming from the analysis of the mean values calculated from the available data is that, for criterion C_9 corresponding to a shots-to-goal ratio, it can be noticed that the values differ significantly for the analyzed seasons. Season 2015/2016 was the least demanding season regarding the number of shots that needed to be made before the goal was scored, which equals about 5.8 shots. On the other hand, the most demanding season regarding the number of shots required to score a goal was the season 2020/2021, where the forwards needed to shoot at target more than 8.5 times to score.

Standard deviation statistical measures allow for identifying the most spread values regarding the analyzed criteria. From Table 4, it can be seen that the most diverse data was observed for the criteria C_1, C_3, and C_{11} corresponding to the mean value of pass success expressed in percents, number of total assists and shots-to-goal ratio. Presented statistical calculations to help to understand and visualize how the data and players' performance differ from season to season.

Table 3. Mean values calculated from the players' performance from the analyzed seasons' data

Mean	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
15/16	75.983	1.161	3.435	2.078	1.139	1.900	9.870	0.422	0.713	1.804	5.879	0.005	0.002
16/17	76.075	1.208	4.875	2.150	1.250	1.963	10.000	0.433	0.692	1.738	7.445	0.004	0.002
17/18	75.000	1.200	4.840	2.008	1.180	2.052	9.200	0.412	0.752	1.632	8.192	0.004	0.002
18/19	75.846	1.121	4.250	1.988	1.117	2.279	10.333	0.421	0.621	1.588	6.309	0.004	0.002
19/20	74.742	1.131	4.192	1.977	1.131	2.154	9.385	0.369	0.754	1.446	7.244	0.004	0.002
20/21	76.835	1.170	5.650	2.065	1.265	2.145	8.800	0.435	0.715	1.475	8.530	0.004	0.002

C1 Pass success percentage, C2 Key passes per game, C3 Total assists, C4 Shots per game, C5 Fouled past per game, C6 Bad control per game, C7 Total goals, C8 Offsides per game, C9 Dribbles per game, C10 Dispossessed per game, C11 Shots to Goal ratio, C12 Goals per minute, C13 Assists per minute

Table 4. Standard deviation (SD) values calculated from the players' performance from the analyzed seasons' data

Season	C1 SD	C2 SD	C3 SD	C4 SD	C5 SD	C6 SD	C7 SD	C8 SD	C9 SD	C10 SD	C11 SD	C12 SD	C13 SD
15/16	6.263	0.553	2.585	0.798	0.559	0.588	6.188	0.248	0.408	0.663	2.144	0.002	0.001
16/17	7.200	0.571	4.014	0.825	0.626	0.601	6.318	0.258	0.442	0.735	5.362	0.002	0.002
17/18	8.336	0.552	3.460	0.817	0.612	0.642	6.800	0.302	0.384	0.751	7.044	0.002	0.001
18/19	6.730	0.393	2.367	0.682	0.572	0.581	5.728	0.234	0.303	0.789	3.369	0.002	0.001
19/20	9.371	0.621	3.942	0.734	0.644	0.643	6.434	0.221	0.394	0.709	3.810	0.003	0.001
20/21	6.945	0.592	3.582	0.711	0.625	0.606	5.627	0.304	0.410	0.523	5.662	0.002	0.001

C1 Pass success percentage, C2 Key passes per game, C3 Total assists, C4 Shots per game, C5 Fouled past per game, C6 Bad control per game, C7 Total goals, C8 Offsides per game, C9 Dribbles per game, C10 Dispossessed per game, C11 Shots to Goal ratio, C12 Goals per minute, C13 Assists per minute

To evaluate the players' performance based on the selected criteria and multi-criteria decision analysis approach, the TOPSIS method is used as the assessment technique. Since the MCDA methods operate based on the determined criteria weights which reflect the importance of each criterion in the problem, it was required to provide the relevance of criteria in the problem. The proposed decision model assumes that each of the selected criteria is equally important in the players' performance. To this end, each weight has an assigned weight value that equals ≈ 0.0769. It allows for determining a decision model that considers every criterion equally relevant in the assessment and requires from the players' good performances in every evaluated area. The first phase of the assessment is directed at obtaining players ranking established based on the presented approach. Then, the sensitivity analysis is performed to verify which part of the games could improve significantly players' performance.

RESULTS

Multi-Criteria Decision Analysis assessment

The application of the TOPSIS method within the determined decision model allowed for obtaining the rankings of players' performance in subsequently analyzed seasons. The rankings are presented in Figure 3, where the number in the cell refers to a position determined from the rating from the multi-criteria evaluation, and X in the cell represents an absence of a player in the given season. What is worth mentioning is that the presented visualization shows that player A_3, who was not playing in the Premier League in the season 2018/2019, was ranked at 1st position in every other season. In season 2018/2019, the best player indicated by the decision model was player A_16, who in the previous season was classified in 3rd position and in two following seasons was placed 4th. It is worth mentioning that his two first seasons in Premier League were not as successful as the rest of them since he was ranked in 10th position in both of them. From the visualization, it can be seen that many players had their ups and downs throughout the analyzed seasons, and their positions varied significantly.

Players rankings

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{26}
2015/2016	8	7	1	3	4	20	11	14	2	16	23	21	5	19	17	10	13	12	15	22	18	6	9	X	X	X
2016/2017	5	19	1	7	4	20	21	12	2	9	14	22	3	X	23	10	15	X	18	11	16	8	6	13	17	24
2017/2018	7	21	1	2	10	23	20	6	4	8	18	24	12	17	25	3	19	14	9	16	X	11	5	15	13	22
2018/2019	6	17	X	2	12	21	15	10	3	13	14	23	5	24	X	1	18	11	19	16	22	20	4	9	7	8
2019/2020	13	10	1	3	11	16	19	6	9	5	23	26	12	20	24	4	21	8	15	18	22	14	2	17	7	25
2020/2021	3	9	1	X	X	14	X	15	5	10	18	X	6	20	17	4	11	12	X	X	19	7	2	13	8	16

Figure 3. The ranking of players in subsequent seasons is determined with the multi-criteria model. Parameters A1 to A26 represent subsequent players.

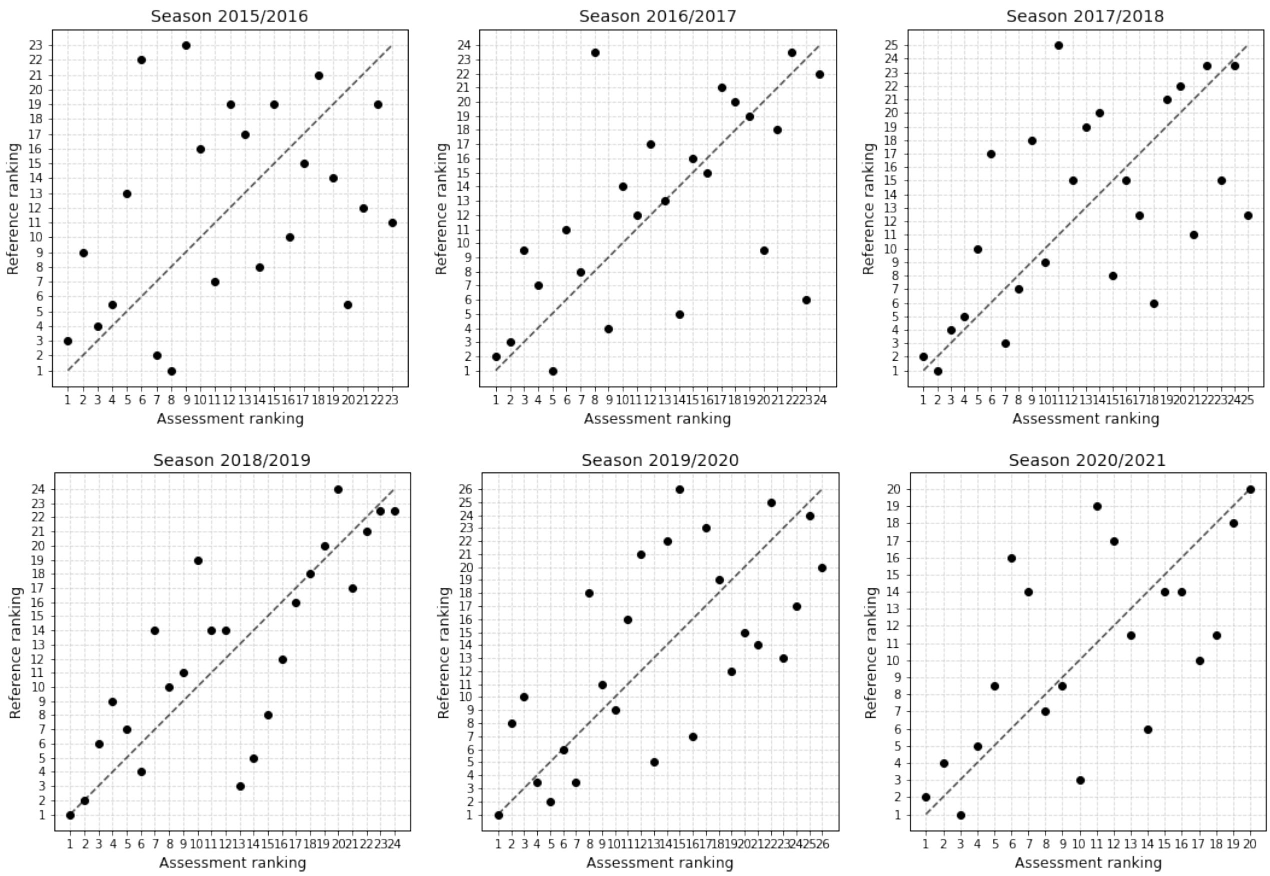

Figure 4. Comparison of players' rankings determined with the designed multi-criteria model and rating from the WhoScored.com statistics [28].

In Figure 4, the comparisons of rankings established based on the multi-criteria model and rating presented in the WhoScored.com statistics [36] were shown. It can be seen that the players' performances in the analyzed seasons are evaluated similarly, especially at the top and at the bottom of the rankings. The most discrepancies regarding the assigned position in both rankings for a given player are visible in the middle of the established order. The reason for the occurring differences can be taking into account slightly different criteria in the assessment process and assigning different relevance to these criteria in the case of calculating the ranking of players by the proposed model and in the ranking published by the WhoScored.com site. However, despite the visible differences in the classification order caused by the different evaluation approaches, it can be seen that the proposed multi-criteria model has reflected the assessment process effectively.

It was worth indicating the similarity of the obtained rankings for all analyzed seasons, presented in Figure 5. The Weighted Spearman (r_W) and WS rank similarity (WS) coefficients were used for this purpose. The visualization presenting the coherence of the results is shown in Figure 5. From the presented flow of the correlation values, it can be seen that the assessments from the decision model produced highly similar rankings to those presented on the WhoScored.com website [36]. The most coherent rankings were obtained for the season 2018/2019, for which the r_W coefficient equaled *0.77*, and the WS coefficient was *0.96*, showing noticeably high similarity. The visible correlation of the ranking was calculated by applying the determined decision model with the reference rankings determined based on the WhoScored.com statistics confirms that the proposed approach can be treated as one of the possible ways for assessing players' performance with high accuracy of the assessment.

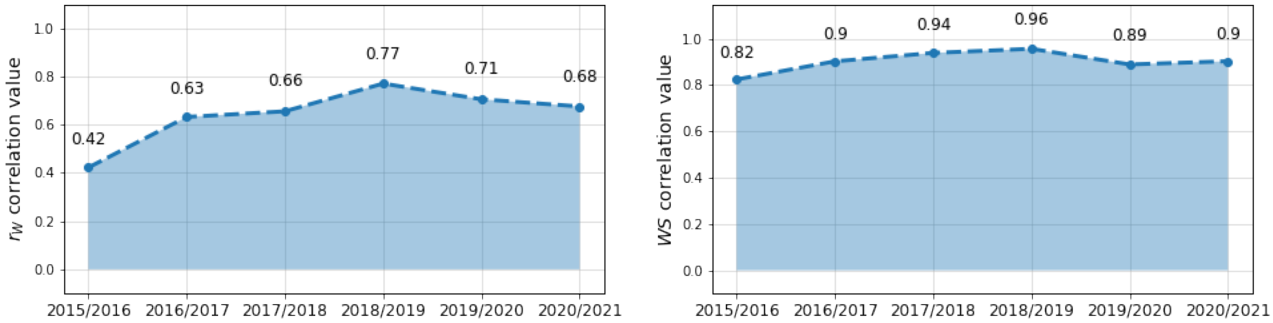

Figure 5. The players' ranking was correlated with the designed multi-criteria model and rating from the WhoScored.com statistics [36].

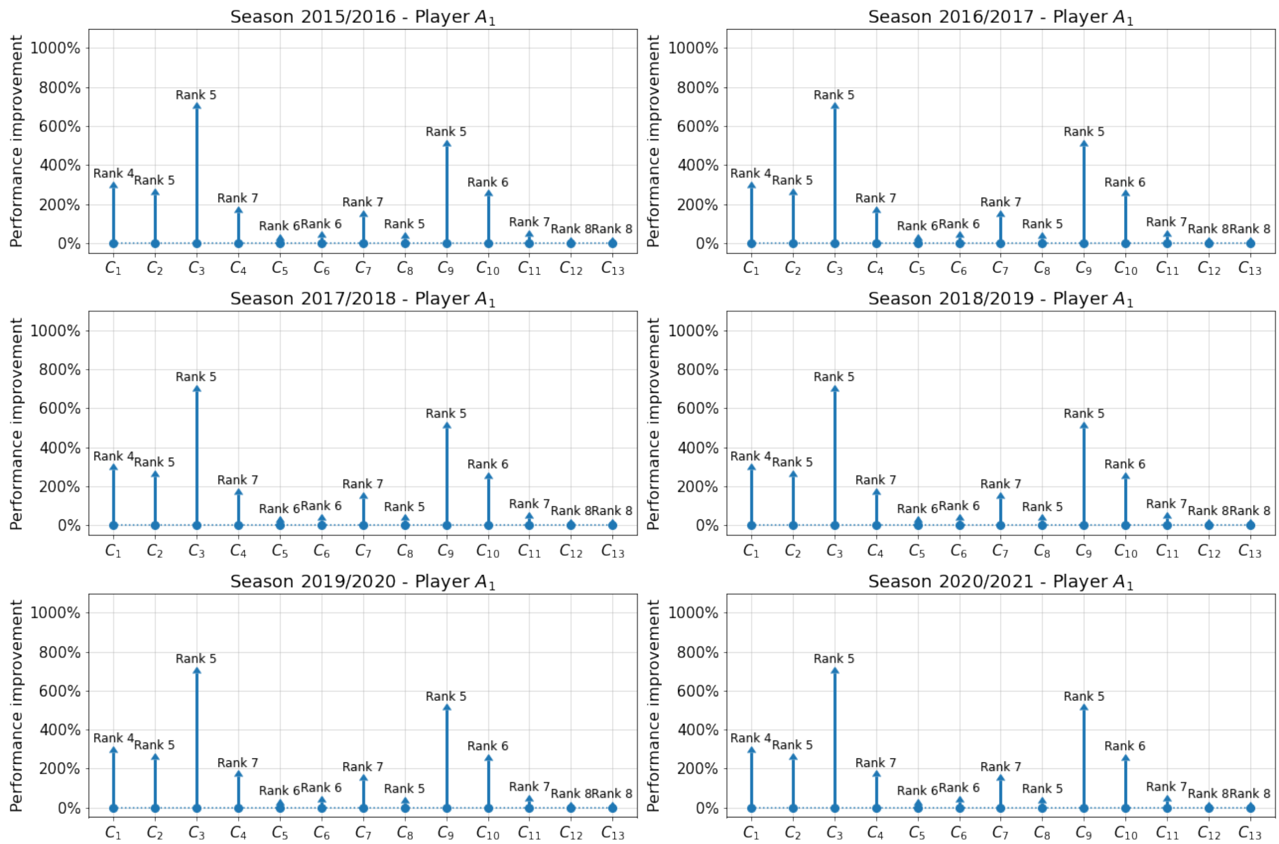

Figure 6. Results of sensitivity analysis of the potential performance improvements for player A_1 throughout the analyzed seasons. The baseline represents the initial position in the ranking: 8th, 5th, 7th, 6th, 13th, and 3rd for subsequent seasons.

Sensitivity analysis evaluation

The next phase of the players' performance assessment included an examination of the robustness of the results to modifications introduced in the decision matrix, which represents the player's performance regarding the considered criteria. To this end, all forwards were examined to indicate which area of games could significantly improve their results compared to others. To show the obtained results of the sensitivity analysis, selected examples of players' assessments throughout the analyzed seasons were presented.

The first presented example concerns the evaluation of player A_1 performance. From Figure 3, it can be seen that he participated in all of the analyzed seasons, with the following positions in ranking determined by the application of the designed decision model: 2015/2015 (8th), 2016/2017 (5th), 2017/2018 (7th), 2018/2019 (6th), 2019/2020 (13th), and 2020/2021 (3rd). Based on that, it can be concluded that his performance allowed him to be placed in the top positions of the ranking for most of the analyzed seasons. Performing the sensitivity analysis on the performance values regarding subsequent criteria taken into account in the problem allowed to indicate what improvements made in the game could increase his rating compared to other players.

The second presented example of the results obtained from the sensitivity analysis of the performance improvement concerns the results for the player A_{16}. From Figure 3 it can be seen that his positions in rankings from the model for subsequent seasons were: 2015/2015 (10th), 2016/2017 (10th), 2017/2018 (3rd), 2018/2019 (1st), 2019/2020 (4th), and 2020/2021 (4th). From this, the significant promotion between the positions in ranking from seasons 2016/2017 and 2017/2018 can be noted.

The last presented example from the performed assessment concerns the results obtained for the player A_{20}. This forward was assessed by the model in the bottom part of the ranking for most of the analyzed seasons, namely 22nd in 2015/2016, 11th in 2016/2017, 16th in 2017/2018, 16th in 2018/2019, 18th in 2019/2020, and in 2020/2021 player was not participating in games in Premier League. In addition, from players' appearances it can be seen, that 13 other strikers had similar situation in which one of the analyzed seasons were left empty in the assessment, since the player did not participate in the Premier League games. The purpose of presenting results obtained for this player is to demonstrate how significant promotions from the bottom of the ranking could be obtained with performance improvements in particular areas. Figure 8 shows the visualization of the analyzed seasons' assessment.

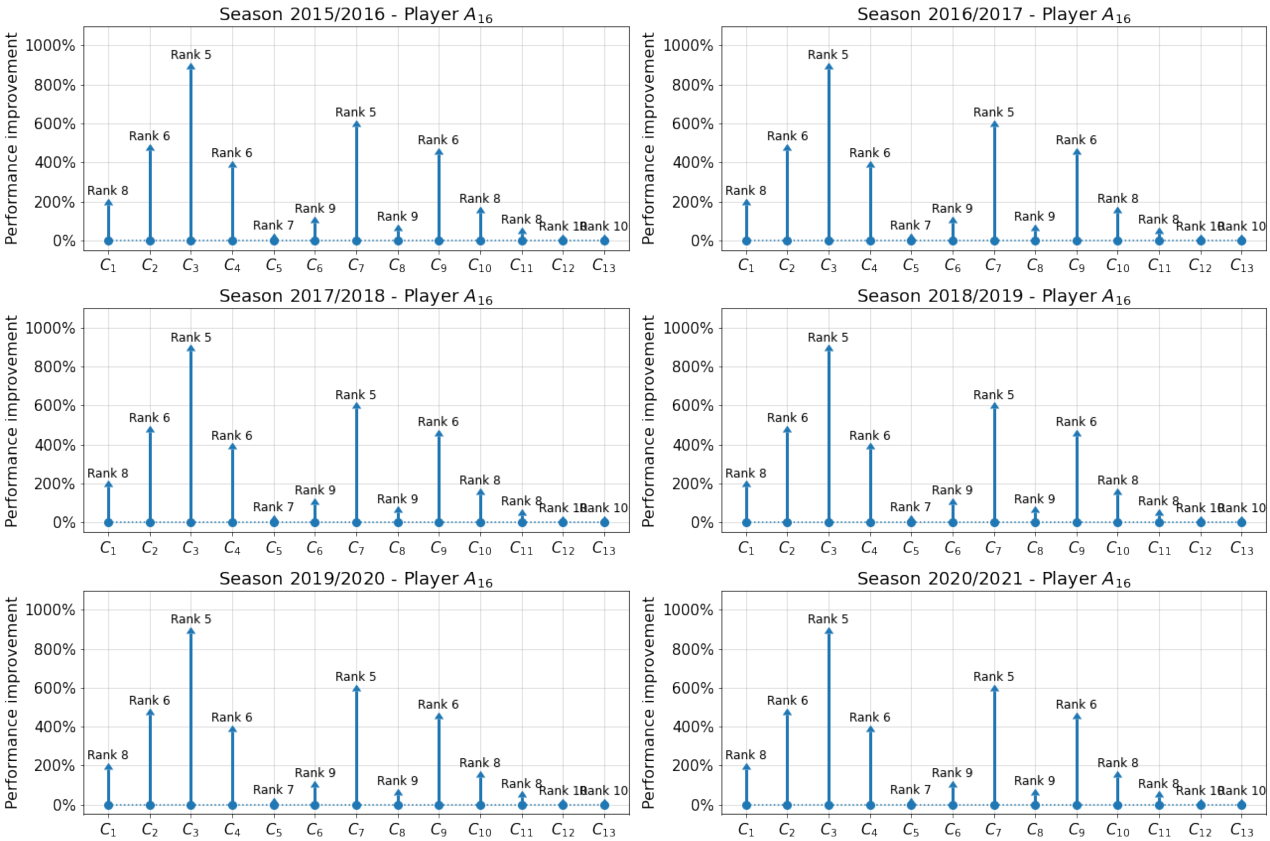

Figure 7. Results of sensitivity analysis of the potential performance improvements for player A_{16} throughout the analyzed seasons. The baseline represents the initial position in the ranking: 10th, 10th, 3rd, 1st, 4th, 4th for subsequent seasons.

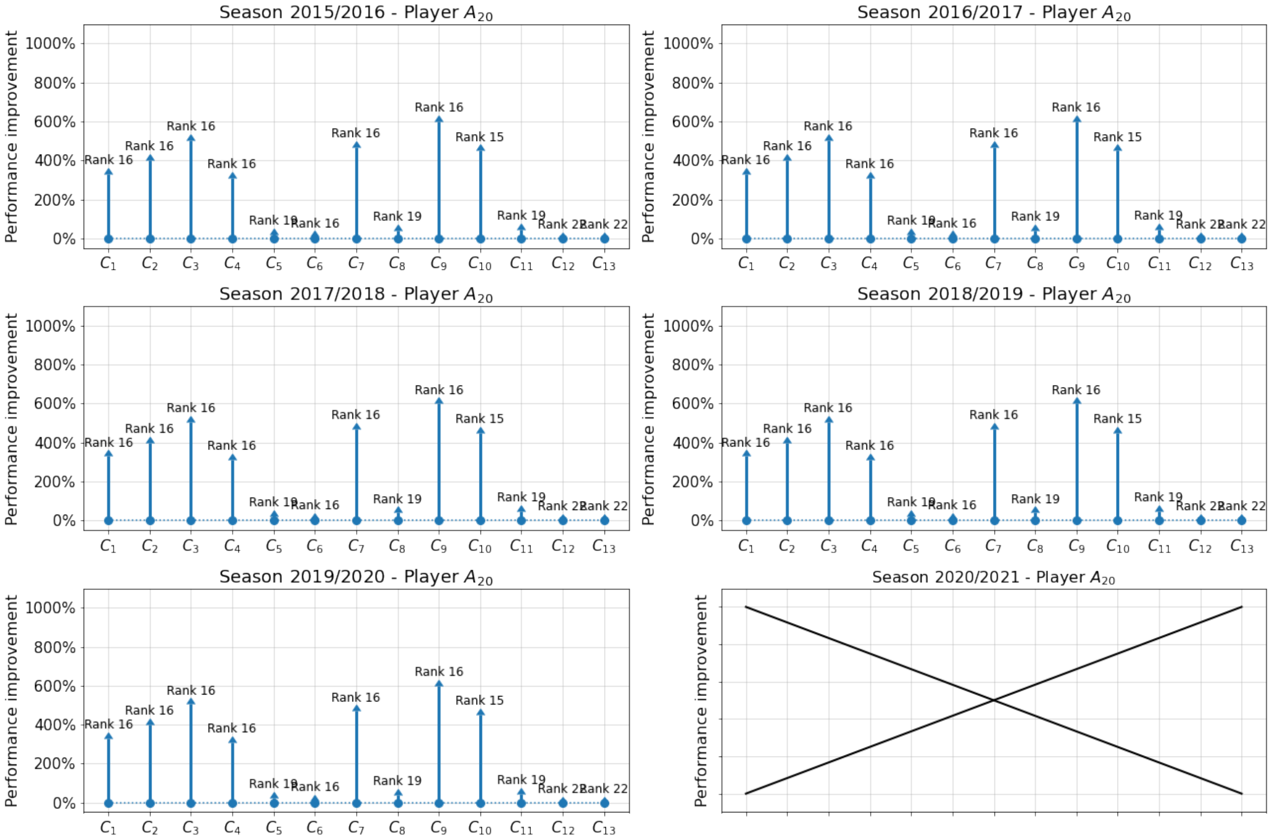

Figure 8. Results of sensitivity analysis of the potential performance improvements for player A_{20} throughout the analyzed seasons. The baseline represents the initial position in the ranking: 22th, 11th, 16th, 16th, 18th for subsequent seasons.

Furthermore, in the proposed research, three selected players performance were discussed to indicate how the striker's performance could be evaluated with the multi-criteria approach. To provide access for the rest of the obtained results from the analysis, the generated visualizations were placed in a publicly available repository [40]. The visualizations of the players assessment were included with a raw data used for the multi-criteria evaluation.

From the performed research on sensitivity analysis of the results and examining the impact of controlled improvements in the players' performance on the position in rankings, it can be seen that the additional information about the potential improvements can be practically used in determining future training goals. Based on the identified areas which could contribute to the biggest promotions in the ranking, the training programs could be more individual and focus on the most important factors for the particular forward, assuring him more effective performance regarding others. However, it should be mentioned that the study considered changing only one parameter at a time for an individual player, indicating the scale of improvement that should be made to promote a forward to a given position. Considering the characteristics of football training, potential improvements could be made in many areas at the time. To this end, the most important areas of evaluation, which assured the most significant promotions, could be combined as the selected training areas on which the particular player should focus.

DISCUSSION

The important point in this study is that all performance criteria are equally weighted, meaning that each criterion contributes equally to the overall player performance rating. However, it is important to bear in mind that in real-life scenarios not all criteria are of equal importance to football clubs. The relative importance of criteria can vary significantly depending on the specific goals and priorities of the club. Therefore, future research should explore the dynamic nature of criterion importance and provide a framework for clubs to adjust criterion weightings according to their unique goals, style of play and team composition. Aligning the weighting system with the club's strategic goals will enable a more nuanced and accurate assessment of player performance, ultimately helping to make more informed decisions about player recruitment, coaching and team tactics.

From the results presented in Figure 6, for the analysis of the player A_1, it can be seen that there are particular areas of game that could provide significant improvements in the player performance. The visualization shows the volume of improvement for the given criterion required to promote a player to a particular position in the ranking. From this, it can be seen that while analyzing the results in season 2015/2016, the potential highest position for the player A_1 could be 4th place while improving the performance regarding the criterion connected to the mean value of pass success in percentage. From the presented visualization, it can be indicated that by improving his performance in this area by about 360% (3.6 times better than the value noted by this player in this area), he could be promoted up by 4 positions in the ranking. It should be mentioned that the examination considered the upper and lower bounds of the modifications, which were set by the 10 times multiplication of the initial value for the profit criteria and by 0 for the cost criteria.

Moreover, it can be seen that despite more significant potential improvements in the performance for criteria C_3 and C_9, they could not assure greater promotion in the ranking than in the case of C_1 for the season 2015/2016. On the other hand, for the season 2016/2017, the biggest potential improvement was possible by being more effective in the area of scoring more goals per minute (C_{12}). It translates into achieving more goals scored in the lower amount of time by the player A_1. It was the biggest required change to promote this player in the ranking by two positions and equaled about 980% of improvement compared to the initial value. However, similarly to the previous analyzed season, there were less demanding changes in the performance that could promote the player A_1 in the ranking to a higher position. It is worth indicating that the sensitivity analysis of the results shows that for the statistic of mean values of offsides per game (C_8) if the player could reduce this value by about 40%, it would allow him to be ranked 2nd, which would be promotion by 3 positions in the ranking. Furthermore, the most valuable promotion in the overall assessment could be achieved by decreasing the mean value of fouled past per game (C_5) by about 20% in the season 2020/2021. It is the lowest required change in this season to promote the A_1 player to the 1st position in the ranking of players. In the practical dimension, it indicates the need to improve his physicality and awareness, which could allow him to be more resistant to attacks from other players on the pitch, thus decreasing the mean values of fouled past per game.

From the analysis of the potential improvements in the player's performance presented in Figure 7, it can be concluded that multiple game areas could be addressed in the training process to make this player better than others. Comparing the seasons 2015/2016 and 2016/2017, it can be seen that the more significant improvement in the ranking position is observed for the second season, where from the 10th position, the player A_{16} could be placed 2nd with the improvement of the mean value of shots per game (C_4) by about 400%. It is worth mentioning that another improvement also assured the promotion to the 2nd position in the forwards ranking for the same season. The mean value of key passes per game (C_2) increased by about 780% could also translate into the significantly better rating of this player. These two changes show the most important aspect of the game that should be improved to be classified as a more effective player in the compared set of forwards.

In the next analyzed season (2017/2018), the player A_{16} was placed at 3rd position in the ranking determined using the proposed decision model. However, the sensitivity analysis of the performance improvement has shown that with certain upgrades in several areas of the game, this forward could be ranked in 1st position.

Namely, improvements in performance regarding six criteria could promote him in the ranking of the considered players. These areas were: successful passes (C_1), key passes per game (C_2), total assists (C_3), shots per game (C_4), dribbles per game (C_9) and dispossessed per game (C_{10}). What is worth noting is that with the established condition of maximum improvement of 10 times multiplication of initial value, for criteria C_{10} - C_{12}, it was not possible to promote the player in the ranking despite the potential performance increase. On the other hand, with the initial 4th place in the ranking for season 2019/2020, it was possible to promote the player A_{16} only to 2nd position for several criteria (C_1, C_2, C_4, C_7, C_9, and C_{10}).

In addition, for two of the analyzed seasons, it can be seen that no potential improvement based on the modified performance can be observed. For the season 2018/2019, the reason is apparent and caused by the fact that the player A_{16} was ranked 1st in the initial assessment, so there was no possibility to upgrade his position in the ranking. In the case of the season 2020/2021, the initial position indicated by the decision model was 4th place. No changes can be observed in the potential position improvements caused by the increased performance. It can be caused by the fact the established limit of 10 times the multiplication of the initial value was too small to promote this player in the ranking. It means that this player performs much worse than the forwards placed in the first three positions in the ranking, and the examined range of improvements would not cause any promotions. In the practical dimension, for 4 of the 6 analyzed seasons, the player A_{16} could improve certain areas of the game to increase his rating. The most important factors of the game that could significantly improve his evaluation were actions connected to passing, assisting, dribbling, and physicality.

From the visualizations presented in Figure 8, it can be seen that the highest potential position achieved by the player A_{20} with modeled improvement was 2nd position in the ranking for the season 2016/2017, considering the 800% performance increase for key passes per game (C_2) and for shots per game (C_4). It translates into the progression of 14 positions in the forwards' ranking (from 16th to 2nd). It is worth mentioning that for some seasons, for selected criteria, a slight improvement of performance regarding the initial value allowed for significant promotion in the ranking of players. For the season 2018/2019, in which the forwards A_{20} was placed in 16th position, only 40% improvement in the area of decreasing the number of bad controls of the ball per game could promote this player to 6th position. It is a noticeable upgrade, which could be caused by increasing ball control skills under pressure, making the player's performance in this area more effective. Another significant improvement could be achieved by increasing this player's physicality, making him more resistant to fouls made by other players. For season 2016/2017, reducing the number of fouls past per game by about 50% would promote the player A_{20} to 9th place. Moreover, it could be seen that for every analyzed season, increasing the number of total goals in a season (C_7) would allow him to progress in the ranking by at least 5 positions (for season 2017/2018), with maximum promotion of 11 positions for season 2016/2017. It shows that this is another important aspect of the game in which this player should develop his skills to be more effective as a forward than others.

From the obtained results of the analysis it can be seen that particular areas of the game could significantly increase the overall rating of the strikers performance. In practical terms, coaches and staff members could gain knowledge of what area of the game should be explored more in the training process to gain advantages in the matches. Showing that decision criteria connected to passing (C_1, C_2, C_3, C_{13}) could increase the quality of the given strikers' performance, the training should be more focused on this particular aspect to improve the players' rating. On the other hand, when scoring more goals ($C_7, C_{11,} C_{12}$) could lead to significant increase of player position in the ranking, the focus should be paid to shooting training sessions, in which strikers could improve their skills and be more prepared to score goals throughout the season. In addition, based on the presented results, the coaches and staff members of football clubs could benefit from particular performance improvements shown in the sensitivity analysis. For example, in case of player A_1 and season 2015/2016, it could be seen that improving the amount of key passes per game (C_3) by about 800% could promote this striker from 8th to 5th position. On the other hand, for season 2020/2021, increasing the number of dribbles per game (C_9) by about 200% could promote this player to 1st position in the ranking. Thus, it could be seen that particular areas could be addressed in the training process to improve skills and make the given striker more successfull in incoming seasons comparing to other players.

Limitations of the study

Firstly, the availability of data posed a limitation. The analysis relied on historical performance data of the players, and the completeness and accuracy of this data could have influenced the results. Additionally, the methodology employed, including the established bounds for performance improvements, may have affected the potential ranking changes. Limiting performance improvements to a maximum of ten times the initial value may not fully capture the realistic potential for player improvement in some criteria. These constraints could impact the practical applicability of the findings.

Furthermore, while the analysis identified key areas for performance improvement, it does not delve into the specific strategies or interventions needed to achieve these improvements. Based on these findings, practical implementation and training recommendations for players looking to enhance their skills are beyond this study's scope. Therefore, a more comprehensive approach involving the development of actionable strategies for player improvement would be a valuable addition to future research in this area.

Lastly, the sensitivity analysis primarily focused on individual player performance, and the interactions and dynamics between team members were not considered. In team sports such as football, player performance is intricately connected with team strategies, tactics, and teammates' performance. Neglecting these interdependencies may provide an incomplete picture of the factors influencing player rankings. Future research could explore more holistic models that consider team dynamics and their impact on individual player performance and rankings.

Practical aspect

- Personalised training programmes: coaches can use the results to adjust training programmes for individual players. By identifying the specific areas where each player can make the most significant improvement, coaches can design personalised training regimens to improve their skills effectively.
- Targeted skills development: For football clubs, these results can guide the development of young talent. Identifying key performance criteria can help clubs prioritise areas of skill development during a player's formative years, increasing the likelihood of producing top-level players.
- Performance evaluation: The survey provides a systematic method of assessing player performance. Clubs can use this as part of the scouting process to evaluate potential players and identify players who can contribute to the success of the team.
- Performance monitoring: Coaches and clubs can use the model to monitor player progress. By tracking performance in identified key areas, they can ensure that players are improving as expected.
- Competitive advantage: football clubs can gain a competitive advantage by using insights to identify undervalued players in the transfer market. A player who excels in key performance criteria may be a hidden talent.

This research provides coaches and clubs with valuable information to make data-driven decisions on player development, recruitment and playing strategy. It offers a more precise and targeted approach to improving player performance, leading to better performance on the pitch and a competitive advantage in football.

Future research directions

This research opens several promising avenues for further research and exploration in sports analytics, particularly in assessing player performance in football. Here are some potential directions for future research:

- Position-specific analysis: Extending the research to assess the performance of players in different positions, such as defenders, midfielders, and goalkeepers, would be valuable. This would involve identifying key position-specific performance criteria and their relative importance.
- Dynamic significance of criteria: Exploring how the importance of performance criteria changes over time or in different leagues or games. Understanding the impact of the relevance of criteria values in different contexts can provide more detailed information.
- The development pathways: Exploring the trajectories of player development over time. Tracking improvements in key performance criteria for individual players as they progress through their careers can provide insight into what drives player development.
- Integration of additional data: Integrate more data sources such as tracking data, injury history and even physiological data for a comprehensive understanding of player performance and health.
- Modification of multiple parameters: In this study, the sensitivity analysis of the striker's performance was done, considering modifying one parameter at a time. To model the real case scenario more accurately, further studies could examine the modification of multiple parameters at a time. Thus, it would be possible to evaluate if improving skills in many areas with lower performanceincrease could lead to similar outcomes.

CONCLUSION

1. Decision-making support systems in sports can increase the efficiency and effectiveness of the development of players individually as well as in the future of entire teams.
2. Analyzing the performance of individual players allows you to identify areas for improvement.
3. Sensitivity analysis showed which aspects of the game are most susceptible to changes affecting the player's ranking.

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APPENDIX

Table 5. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2015/2016)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	73.1	1.2	1	4.2	1.4	1.8	25	0.8	0.3	2.4	6.3840	0.0074	0.0003
A_2	65.8	1.3	6	3.2	0.8	1.8	24	0.7	0.5	0.8	4.8000	0.0076	0.0019
A_3	78.3	3.2	9	2.0	0.7	1.7	7	0.3	1.9	1.4	6.2857	0.0035	0.0045
A_4	84.7	0.9	2	4.0	1.2	2.0	24	0.9	0.6	3.4	4.8333	0.0101	0.0008
A_5	75.9	1.7	9	2.2	2.0	2.5	10	0.2	1.2	2.5	6.1600	0.0040	0.0036
A_6	69.6	0.9	3	2.1	1.3	2.5	8	0.4	0.7	1.3	6.0375	0.0039	0.0015
A_7	60.9	1.5	7	2.5	0.9	1.8	13	0.5	0.6	1.6	6.9231	0.0039	0.0021
A_8	76.7	1.2	4	1.8	1.8	2.4	11	0.5	0.6	3.1	4.7455	0.0042	0.0015
A_9	76.6	1.6	7	2.0	0.6	1.8	10	0.5	0.9	2.1	4.8000	0.0050	0.0035
A_{10}	80.8	1.1	6	2.3	1.9	2.6	11	0.7	0.5	1.6	6.2727	0.0042	0.0023
A_{11}	76.7	1.2	1	0.9	2.6	2.4	2	0.2	0.4	2.5	13.5000	0.0008	0.0004
A_{12}	66.4	1.2	4	2.3	1.4	2.3	10	0.9	0.6	1.5	5.2900	0.0047	0.0019
A_{13}	78.9	1.6	3	2.4	0.6	1.6	11	0.1	1.3	1.3	6.9818	0.0038	0.0010
A_{14}	80.9	0.6	0	2.0	1.3	3.2	7	0.3	0.7	2.5	7.7143	0.0030	0.0000
A_{15}	66.1	1.1	3	2.1	0.9	1.7	9	0.6	0.1	1.1	3.2667	0.0059	0.0020
A_{16}	85.3	1.1	2	1.7	1.7	1.2	6	0.2	0.7	2.1	6.5167	0.0031	0.0010
A_{17}	77.5	1.3	3	1.5	0.8	1.4	6	0.2	0.8	1.3	6.0000	0.0026	0.0013
A_{18}	75.6	0.9	2	1.5	1.1	1.6	6	0.1	1.2	1.9	5.5000	0.0029	0.0010
A_{19}	84.7	0.6	1	1.2	0.8	1.5	4	0.2	1.2	1.0	5.7000	0.0024	0.0006
A_{20}	76.9	0.8	2	1.8	0.9	2.8	6	0.5	0.4	1.6	7.2000	0.0031	0.0010
A_{21}	79.7	0.6	2	1.6	0.9	1.3	5	0.5	0.3	1.1	4.8000	0.0036	0.0015
A_{22}	76.9	0.5	1	1.1	0.2	1.0	8	0.1	0.2	1.5	0.9625	0.0106	0.0013
A_{23}	79.6	0.6	1	1.4	0.4	0.8	4	0.3	0.7	1.9	4.5500	0.0036	0.0009

Parameters A1 to A20 represent subsequent players. Parameters: (C1 Pass success percentage, C2 Key passes per game, C3 Total assists, C4 Shots per game, C5 Fouled past per game, C6 Bad control per game, C7 Total goals, C8 Offsides per game, C9 Dribbles per game, C10 Dispossessed per game, C11 Shots to Goal ratio, C12 Goals per minute, C13 Assists per minute)

Table 6. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2016/2017)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	71.7	1.4	7	3.7	1.5	2.8	29	0.6	0.3	1.6	3.7000	0.0114	0.0028
A_2	82.0	2.9	18	2.4	1.1	1.6	6	0.1	1.8	1.3	13.2000	0.0021	0.0062
A_3	79.4	2.2	7	2.9	0.9	2.3	11	0.5	1.5	2.3	8.9636	0.0036	0.0023
A_4	77.5	1.6	5	2.1	2.0	2.2	13	0.5	0.7	2.7	4.2000	0.0058	0.0022
A_5	79.9	1.1	9	1.4	3.5	3.3	7	0.2	1.2	3.7	6.8000	0.0023	0.0030
A_6	59.6	0.9	2	2.9	1.3	2.6	15	1.0	0.4	1.8	6.9600	0.0048	0.0006
A_7	80.7	1.4	7	2.5	2.1	2.2	18	0.3	1.2	2.1	4.8611	0.0059	0.0023
A_8	82.4	1.0	3	4.5	1.1	2.5	20	0.7	0.6	2.2	5.6250	0.0083	0.0012
A_9	73.0	1.1	3	2.7	1.7	2.4	9	0.7	0.7	1.9	8.7000	0.0037	0.0012
A_{10}	77.0	2.1	13	3.1	0.9	2.1	9	0.0	0.8	1.1	12.7444	0.0027	0.0039
A_{11}	81.2	1.3	6	2.4	0.9	1.6	14	0.6	0.6	1.8	3.9429	0.0068	0.0029
A_{12}	79.6	0.8	2	1.9	1.2	2.8	16	0.1	0.7	2.5	3.6812	0.0059	0.0007
A_{13}	75.2	1.4	4	1.6	1.0	1.7	3	0.1	1.5	2.2	16.0000	0.0012	0.0016
A_{14}	80.4	1.4	6	1.9	1.6	1.8	7	0.5	1.0	2.6	7.8714	0.0028	0.0024
A_{15}	75.3	0.5	2	2.2	1.0	2.0	10	0.6	0.6	1.4	5.0600	0.0052	0.0010
A_{16}	82.7	1.5	1	2.2	1.2	1.1	7	0.4	0.6	1.8	10.0571	0.0024	0.0003
A_{17}	81.3	1.0	6	1.7	1.1	1.6	4	0.2	0.4	1.6	7.6500	0.0026	0.0039
A_{18}	58.5	1.1	4	1.1	0.7	1.8	10	0.5	0.3	1.0	3.4100	0.0034	0.0014
A_{19}	62.5	0.9	5	1.5	0.8	1.7	13	0.7	0.3	0.7	3.8077	0.0046	0.0018
A_{20}	87.9	1.2	2	1.5	0.8	1.1	1	0.2	0.4	0.8	27.0000	0.0007	0.0015
A_{21}	78.7	0.7	1	1.4	1.0	1.5	5	0.3	0.3	1.2	4.4800	0.0029	0.0006
A_{22}	72.8	0.4	0	1.6	1.3	2.4	6	0.9	0.3	2.0	4.2667	0.0044	0.0000
A_{23}	76.6	0.7	3	1.1	0.1	1.0	4	0.3	0.2	1.0	1.3750	0.0076	0.0057
A_{24}	69.9	0.4	1	1.3	1.2	1.0	3	0.4	0.2	0.4	4.3333	0.0024	0.0008

Table 7. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2017/2018)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	82.8	1.6	6	3.8	0.7	2.2	21	0.6	0.6	1.7	3.9810	0.0107	0.0030
A_2	83.4	2.9	16	2.5	0.9	1.7	8	0.1	1.5	1.6	11.2500	0.0026	0.0052
A_3	71.2	0.9	2	5.0	1.1	1.7	30	1.1	0.3	1.6	5.8333	0.0097	0.0006
A_4	84.0	1.7	11	2.6	1.8	2.0	18	0.6	0.9	1.8	4.1889	0.0069	0.0042
A_5	72.6	1.5	7	2.3	0.5	2.2	15	0.4	1.4	1.9	4.9067	0.0054	0.0025
A_6	75.3	1.8	3	2.2	2.6	3.7	9	0.7	0.7	3.8	6.8444	0.0035	0.0012
A_7	80.4	1.7	7	2.4	1.7	2.4	10	0.4	0.7	1.7	6.7200	0.0045	0.0032
A_8	78.6	1.8	7	1.7	1.3	2.4	2	0.2	1.4	2.0	29.7500	0.0006	0.0022
A_9	77.2	1.8	10	1.9	2.3	2.7	9	0.1	0.7	2.5	7.1778	0.0030	0.0034
A_{10}	85.2	1.1	6	2.0	0.7	1.8	12	0.7	0.7	1.5	4.5000	0.0052	0.0026
A_{11}	60.5	0.9	1	1.9	0.7	1.7	20	1.2	0.2	0.4	3.5150	0.0061	0.0003
A_{12}	82.6	0.4	2	1.8	2.4	3.0	7	0.2	1.1	2.9	8.4857	0.0024	0.0007
A_{13}	56.4	0.9	5	1.9	0.9	2.8	3	0.4	0.5	1.0	15.2000	0.0013	0.0022
A_{14}	67.8	0.7	1	1.6	1.4	2.6	3	0.3	0.5	2.0	8.5333	0.0022	0.0007
A_{15}	74.9	1.4	3	1.4	0.6	2.0	4	0.0	1.5	0.9	8.7500	0.0018	0.0013
A_{16}	72.9	1.2	3	1.5	1.7	2.6	8	0.1	0.7	2.5	5.0625	0.0033	0.0012
A_{17}	81.9	1.1	5	1.6	0.9	1.8	9	0.3	0.3	1.8	3.2000	0.0057	0.0032
A_{18}	87.8	0.8	5	1.7	1.1	1.5	8	0.1	0.7	0.6	4.2500	0.0044	0.0027
A_{19}	78.3	0.6	5	1.7	0.5	1.3	7	0.3	0.3	0.9	4.1286	0.0039	0.0028
A_{20}	71.3	1.0	5	1.7	1.5	2.4	8	0.4	1.2	1.9	5.9500	0.0032	0.0020
A_{21}	76.7	1.4	3	1.4	0.6	1.2	1	0.1	0.6	1.4	30.8000	0.0005	0.0015
A_{22}	56.6	0.9	2	1.2	0.6	0.8	5	0.6	0.3	1.0	4.8000	0.0027	0.0011
A_{23}	70.5	0.7	2	1.9	1.3	2.1	8	0.7	0.5	1.7	5.4625	0.0040	0.0010
A_{24}	66.8	0.7	1	1.1	1.3	1.5	2	0.5	0.7	1.0	8.2500	0.0013	0.0006
A_{25}	79.3	0.5	3	1.4	0.4	1.2	3	0.2	0.8	0.7	3.2667	0.0036	0.0036

Table 8. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2018/2019)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	85.8	1.9	10	2.3	1.3	2.2	17	0.4	0.5	2.6	4.1941	0.0061	0.0036
A_2	85.0	1.0	8	3.6	0.8	2.2	21	0.8	0.1	1.6	5.3143	0.0085	0.0032
A_3	78.2	1.3	1	2.4	1.8	2.9	22	0.7	0.8	1.3	3.8182	0.0071	0.0003
A_4	73.1	1.1	4	3.6	1.9	2.9	17	0.4	0.5	1.6	5.7176	0.0070	0.0016
A_5	77.3	1.6	5	2.1	3.0	3.6	10	0.5	0.6	4.2	7.1400	0.0033	0.0016
A_6	80.8	1.3	6	2.2	0.3	2.3	12	0.2	0.8	1.8	5.6833	0.0046	0.0023
A_7	76.2	1.9	6	2.3	1.0	2.1	13	0.1	0.8	0.8	6.3692	0.0041	0.0019
A_8	60.7	1.3	5	2.0	1.1	1.9	9	0.4	0.8	1.1	6.2222	0.0035	0.0020
A_9	85.6	1.1	6	2.4	0.6	1.9	12	0.7	0.8	1.4	4.6000	0.0059	0.0029
A_{10}	67.1	1.0	9	2.2	1.1	3.2	14	0.6	0.3	1.5	4.5571	0.0055	0.0036
A_{11}	78.8	1.6	4	1.7	1.5	2.1	6	0.2	1.4	2.0	9.6333	0.0020	0.0013
A_{12}	72.0	1.1	3	2.1	1.3	3.2	12	0.2	0.6	2.7	5.9500	0.0040	0.0010
A_{13}	78.1	1.2	6	2.5	1.6	2.5	10	0.5	0.7	1.4	6.5000	0.0043	0.0026
A_{14}	75.9	1.2	2	1.5	1.1	2.7	12	0.2	1.2	2.1	4.2500	0.0041	0.0007
A_{15}	80.3	1.1	3	1.6	0.8	2.0	5	0.1	0.8	1.2	7.0400	0.0027	0.0016
A_{16}	65.6	0.9	4	2.3	0.6	1.5	18	1.1	0.4	0.6	3.8333	0.0066	0.0015
A_{17}	68.1	0.7	4	2.0	1.3	2.5	6	0.3	0.2	2.1	7.3333	0.0029	0.0019
A_{18}	75.4	1.4	4	1.9	0.7	2.2	6	0.4	0.7	2.1	11.4000	0.0018	0.0012
A_{19}	79.3	1.3	2	1.4	1.0	1.7	10	0.2	0.4	1.2	2.5200	0.0062	0.0012
A_{20}	85.7	0.6	2	1.2	0.9	1.6	4	0.3	0.8	0.7	5.7000	0.0024	0.0012
A_{21}	72.6	0.6	2	1.2	0.7	2.1	5	0.5	0.4	1.0	5.7600	0.0024	0.0009
A_{22}	64.6	0.5	1	1.2	0.9	2.0	5	0.5	0.5	0.8	2.8800	0.0039	0.0008
A_{23}	77.7	0.8	2	1.4	1.3	2.4	1	0.5	0.7	1.6	19.6000	0.0008	0.0017
A_{24}	76.4	0.4	3	0.6	0.2	1.0	1	0.3	0.1	0.7	5.4000	0.0011	0.0032

Table 9. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2019/2020).

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	81.5	3.9	20	2.8	0.8	1.3	13	0.1	1.4	0.9	6.8923	0.0046	0.0071
A_2	81.6	1.7	7	2.2	1.5	2.9	18	0.4	0.8	1.6	3.7889	0.0065	0.0025
A_3	82.8	1.5	1	3.0	1.2	2.0	20	0.4	0.7	1.8	4.5000	0.0075	0.0004
A_4	77.3	1.1	7	3.1	1.5	2.1	17	0.4	0.5	1.1	5.6529	0.0064	0.0026
A_5	66.7	0.9	2	2.8	1.5	2.3	18	0.7	0.4	1.1	4.5111	0.0069	0.0008
A_6	80.6	0.9	6	2.5	1.3	2.3	17	0.4	0.5	1.9	4.5588	0.0064	0.0023
A_7	68.4	1.1	3	2.8	1.5	3.0	10	0.5	0.4	1.9	5.3200	0.0056	0.0017
A_8	84.7	1.4	10	2.7	0.9	2.2	11	0.6	1.6	1.9	6.8727	0.0044	0.0040
A_9	70.6	0.9	5	2.5	0.3	1.5	23	0.8	0.1	0.5	3.6957	0.0076	0.0016
A_{10}	80.5	0.8	3	3.2	0.4	1.4	16	0.3	0.3	1.3	3.6000	0.0110	0.0021
A_{11}	79.6	1.4	8	2.6	0.4	2.4	9	0.2	0.9	1.0	9.8222	0.0030	0.0027
A_{12}	54.2	1.1	2	1.7	1.3	1.9	10	0.4	0.9	1.0	4.4200	0.0045	0.0009
A_{13}	81.1	0.9	3	1.6	3.2	3.4	4	0.4	1.0	3.9	14.8000	0.0012	0.0009
A_{14}	73.7	1.2	4	1.8	1.0	2.3	4	0.2	1.1	1.6	14.4000	0.0014	0.0014
A_{15}	81.3	0.8	2	1.6	2.8	3.1	9	0.2	0.9	2.6	6.5778	0.0028	0.0006
A_{16}	76.3	0.9	4	1.7	1.3	2.0	8	0.2	1.0	1.6	4.4625	0.0043	0.0022
A_{17}	54.3	0.8	1	1.7	0.8	2.0	2	0.5	0.4	1.0	11.0500	0.0016	0.0008
A_{18}	79.7	0.8	4	1.4	0.9	1.9	8	0.2	1.4	1.8	4.5500	0.0040	0.0020
A_{19}	72.3	1.2	4	1.0	1.0	3.0	6	0.3	0.5	2.1	4.0000	0.0030	0.0020
A_{20}	54.1	0.8	2	1.3	1.0	2.2	2	0.5	0.5	0.8	9.7500	0.0014	0.0014
A_{21}	83.4	1.5	3	1.3	0.7	1.2	2	0.1	1.5	0.7	18.2000	0.0008	0.0012
A_{22}	80.9	0.8	3	1.8	0.7	2.6	5	0.5	0.4	1.1	4.3200	0.0052	0.0031
A_{23}	76.6	0.5	1	0.5	1.1	1.3	1	0.0	0.9	1.5	7.0000	0.0008	0.0008
A_{24}	64.5	0.8	1	1.6	1.1	3.1	8	0.9	0.4	1.5	6.4000	0.0027	0.0003
A_{25}	68.9	0.8	3	1.2	0.7	1.5	2	0.4	0.5	0.9	10.2000	0.0015	0.0023
A_{26}	87.7	0.9	0	1.0	0.5	1.1	1	0.0	0.6	0.5	9.0000	0.0011	0.0000

Table 10. Decision matrix defined for the problem of offensive football players' performance evaluation (Season 2020/2021)

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_1
A_1	69.9	1.4	14	3.9	1.7	1.8	23	0.4	0.5	1.5	5.9348	0.0075	0.0045
A_2	81.7	3.2	12	3.2	1.2	1.8	6	0.0	1.4	1.3	12.2667	0.0030	0.0060
A_3	78.7	1.7	7	2.7	2.2	2.9	11	0.9	0.6	1.7	7.6091	0.0039	0.0025
A_4	83.4	2.0	10	1.8	1.5	1.6	17	0.4	1.5	1.4	3.8118	0.0054	0.0032
A_5	86.2	1.3	7	2.3	1.3	2.0	10	0.3	0.2	2.7	6.4400	0.0039	0.0028
A_6	68.2	1.0	5	2.4	1.5	3.0	10	0.6	0.2	1.9	5.7600	0.0050	0.0025
A_7	82.1	1.2	9	2.1	1.1	2.1	11	0.7	0.5	1.4	6.3000	0.0038	0.0031
A_8	80.7	1.2	7	2.3	0.4	2.2	9	0.1	0.7	1.3	8.4333	0.0032	0.0025
A_9	67.5	0.8	9	2.4	0.7	1.7	15	1.1	0.4	0.4	4.9600	0.0053	0.0032
A_{10}	58.6	0.5	1	2.4	0.7	2.0	10	0.5	0.2	0.9	5.0400	0.0055	0.0005
A_{11}	73.7	1.2	5	1.1	1.6	1.4	1	0.1	1.4	1.6	27.5000	0.0004	0.0022
A_{12}	78.3	1.0	2	2.0	2.9	3.6	11	0.7	0.6	2.6	5.2727	0.0042	0.0008
A_{13}	79.8	1.1	2	2.4	0.5	2.3	12	0.4	0.5	1.4	3.2000	0.0082	0.0014
A_{14}	84.4	0.8	3	2.0	1.2	2.3	4	0.7	0.5	1.7	8.5000	0.0027	0.0020
A_{15}	69.5	0.7	5	1.9	1.6	2.8	12	0.8	0.4	1.5	3.6417	0.0058	0.0024
A_{16}	85.0	1.2	5	1.4	0.5	1.3	6	0.0	0.9	0.8	5.6000	0.0027	0.0022
A_{17}	76.8	0.9	1	1.2	0.9	1.5	2	0.3	1.4	1.0	9.0000	0.0015	0.0008
A_{18}	74.4	0.8	3	1.4	1.4	2.7	3	0.4	1.0	1.3	9.3333	0.0018	0.0018
A_{19}	76.8	1.0	3	1.6	0.5	1.4	2	0.1	0.6	1.3	13.6000	0.0012	0.0017
A_{20}	81.0	0.4	3	0.8	1.9	2.5	1	0.2	0.8	1.8	18.4000	0.0005	0.0014