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Integrating Hybrid FAHP–FRADAR Approach and the FMEA Framework for Evidence-Informed Risk Assessment in Football Player Transfers

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Abstract: This study established a methodology for assessing risk in football player transfers to help football club management make decisions. The proposed model is based on the Failure Mode and Effects Analysis (FMEA) framework, which is expanded by incorporating two Multi-Attribute Decision-Making (MADM) techniques: the Fuzzy Analytic Hierarchy Process (FAHP) was utilized to assign weights to risk factors, and the Fuzzy RAnking based on Distances And Range (FRADAR) method was used to rank potential football player transfers. The proposed model is analogous to FMEA, but instead of the traditional risk factors severity, occurrence, and detection, risk factors tailored to the given problem are used: player market value (as severity), frequency of club changes or a player's injury history (as occurrence), and adaptability to various tactics and playing styles (as detection). The primary objective of this study is to develop a sufficiently reliable model that is flexible enough to be applied in other sports and in various areas of management. The quality of available data and the assessments made by decision-makers, which rely on their experience, knowledge, and subjective judgment, play a crucial role in implementing the proposed model. The model was tested on a random sample of five football players, all central defenders, who are members of one of the five highest-ranked football leagues in Europe.

Keywords: football player transfers, decision-making, FAHP, FMEA, FRADAR

1. Introduction

In today's professional football, player transfers are a complex and high-risk process that requires large financial investment and careful strategic planning. These decisions directly affect a club's success, financial stability, and overall reputation. Even after rigorous scouting and performance analysis, the risk of a failed transfer is still considerable, whether due to poor player adaptation, financial setbacks, or tactical mismatches. Given these limitations, the use of a systematic risk assessment strategy is critical to minimizing uncertainty and increasing the likelihood of a successful transfer.

This need is even more pressing in teams and leagues with limited resources, as a single failed transfer can have a huge impact on sporting performance and financial stability.

One method that provides a structured and analytical approach to assessing transfer risks is Failure Mode and Effects Analysis (FMEA).

FMEA originated in the automotive industry and is used to identify and analyze potential design and manufacturing failures/problems to minimize their impact. The cornerstone of FMEA [1] is the assessment of the severity, occurrence, and detectability of possible problems, which enables organizations to identify significant risk areas and efficiently deploy resources to address them. A similar technique can be applied to the risk assessment of football player transfers, just as risks are identified and investigated in the automotive industry to ensure the necessary product quality and reliability of the manufacturing process. The main objective of this research is to apply the FMEA framework to evaluate possible signings for football clubs.

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1.1. Adapting the FMEA framework to football player transfers

To clarify the principle of the proposed methodology, it is essential to explain the analogy of the proposed model with FMEA. Standard FMEA is based on the identification, evaluation, and analysis of potential failure modes, whether during the product design phase, the production process phase, or the customer use phase. FMEA is used in various industries, such as automotive [2, 3], energy [4], eco-management [5], and software [6], among other fields.

In the automobile industry, which is known for its precision and severe safety regulations, all companies throughout the supply chain are required to perform FMEA. This includes everything from raw materials and semifinished products to components and assemblies.

Risk assessment, also known as reliability evaluation, involves examining three important risk factors: severity (S), occurrence (O), and detection (D). These criteria serve as the foundation for identifying and resolving potential difficulties, maintaining product quality and safety, and reducing operational disruptions.

In FMEA, risk factor S represents the severity of the effects of a failure. It is used to determine the potential impact of a fault or problem on the system, end users, or organizational goals. A higher severity rating implies a failure mode that could cause major disruptions, financial losses, or safety problems.

In the context of football player transfers, risk factor S corresponds to the player's price. The financial investment in a high-priced player reflects the potential severity of the risk involved if the transfer does not succeed. Similar to a high-severity failure in FMEA that results in substantial operational or financial harm, a costly transfer gone wrong could have a considerable negative impact on the club's budget and performance outcomes.

Risk factor O in FMEA assesses the likelihood of occurrence of a specific failure mode. It is a predictive metric that assesses the frequency or likelihood of failure using previous data or observable trends. A higher occurrence score indicates a more common or recurring problem that requires attentive mitigating strategies.

In football, risk factor O is represented in a player's injury history or frequency of club changes. Frequent transfers may indicate problems adapting to team cultures or an inability to develop long-term compatibility, whereas recurring injuries raise reliability concerns. These patterns of instability are similar to recurring failure modes in industrial processes, which represent hazards requiring strategic intervention.

In FMEA, the risk factor D refers to the ability to detect potential failure modes before they lead to specific consequences. A high value of the D factor indicates that the failure mode is very difficult to detect in time. Conversely, a low value means that the failure mode can be easily or automatically identified.

For football players, risk factor D represents their flexibility to different strategies and playing styles. Players who can easily adapt to diverse tactical demands pose a low risk, since their versatility allows managers to efficiently integrate them into various game plans. This is similar to identifying and fixing possible failures before they escalate in an FMEA, leading to smoother operations and better outcomes.

1.2. Risk management in football player transfers

Previous studies have examined various factors that influence the risk connected with football player transfers, indirectly reinforcing the importance of the model presented here. For example, Carling et al. [7] found that players who had just joined a professional football club were at higher risk of injury, particularly in the first season after the transfer. These findings highlight the need to measure the athletes' physical condition during transfers as a key component of the risk assessment process.

In a similar context, Dinsdale and Gallagher [8] created a model that accurately predicts how transfers affect team performance. Their analytical framework provides useful insights into assessing the effects of transfer, which are critical for understanding how transfers affect team dynamics and overall risk. The authors used neural networks to accomplish this task.

Wand [9] used trade network analysis to examine the football player transfer market, gaining a more in-depth understanding of the relationships and forces that influence the market. The analysis used data from the well-known website transfermarkt.co.uk.

The quantitative approach developed by Pantuso and Hvattum [10] is employed to provide analytical support to club managers in forming a team with optimal performance and adapting to different club budgets. In other words, this model aids in making informed transfer-related decisions.

All of these studies establish a good framework for understanding the risks associated with football player transfers, highlighting their significance. In light of this study, the above findings emphasize the importance of building a model for risk assessment and transfer prioritization using quantitative methods. Based on the aforementioned studies, this study confirms the need for an objective approach to transfer decision-making, which is the main contribution of this study.

1.3. Determining risk priorities in football player transfers

Conventional FMEA has numerous drawbacks, particularly in the risk analysis process. Although this method is very useful in industrial practice, many studies have shown that the risk assessment procedure itself needs improvement.

The risk assessment procedure in conventional FMEA is highly complex and demands an in-depth understanding of the problem, expert knowledge, recorded data, and time required to perform the analysis. However, the method used to determine the risk level is highly questionable. It is based on a simple mathematical model that multiplies the values of risk factors S, O, and D to determine the Risk Priority Number (RPN). The risk factors are assessed on a scale of 1 to 10, meaning the RPN value ranges from 1 to 1000. Some limitations of this approach include the boundaries used to determine the risk level (low, medium, and high), making it impossible to define the middle of this scale. Furthermore, by multiplying these three values, only 120 values on the RPN scale are obtained, not all possible values between 1 and 1000. Moreover, conventional FMEA assumes that these three risk factors are of equal importance, a point that is contested by many authors [2, 11]. These are just some of the shortcomings, and further explanations and details can be found in the relevant literature [12].

To overcome these limitations, various approaches have been proposed by different authors. First, some authors consider that risk factors have different degrees of importance [2]. Additionally, to address the limitations related to measurement scales and risk prioritization, the authors apply fuzzy set theory as well as various Multi-Attribute Decision-Making (MADM) methods [13, 14]. Numerous studies have combined these two approaches [15] to effectively overcome the aforementioned drawbacks in a mathematically grounded and reliable manner.

This article proposes a new model for evaluating the risk of football player transfers. The model determines the weights of risk factors based on the Fuzzy Analytic Hierarchy Process (FAHP) [16] and uses the Fuzzy RAnking based on the Distances And Range (FRADAR) [17, 18] method to rank the risk value of potential football player transfers.

In this way, the proposed approach not only provides a mathematical basis for decision-making but also allows for adaptation to different contexts and management requirements. The primary purpose of using this approach is to help reduce the risks associated with football player transfers while also optimizing the decision-making process in professional football.

The article is structured as follows: First, the Introduction includes a review of the relevant literature; the Methodology is described in Section 2 Section 3 describes the proposed algorithm, including the procedure for applying the proposed model. Section 4 includes a case study. The last section summarizes the research findings.

2. Methodology

This research proposes a novel model for analyzing the risks associated with football player transfers that combines the FAHP and FRADAR methods. This integrated strategy attempts to develop a clear sequence for addressing transfer objectives, with a particular emphasis on risk factors that influence the transfer process. This methodology tries to make decision-making easier for club managers.

Potential transfers, i.e., players, $i, i = 1, \ldots, I$, are evaluated based on three risk factors (criteria), $k, k = 1, \ldots, K$:

- Severity (S) – player's market value/transfer value (it may also include the player's total salary throughout the contract or for a specific period of time) ($k = 1$)
- Occurrence (O) – frequency of club changes or the injury history of a player ($k = 2$)
- Detection (D) – adaptability to various tactics and playing styles ($k = 3$)

By combining these MADM methods and criteria (the FMEA framework), the proposed model provides a more refined and quantitatively grounded approach to transfer decision-making, allowing for more adaptability to diverse financial profiles and club requirements.

The primary purpose of this strategy is not just to reduce the risks involved with player transfers but also to optimize the club's success on and off the field.

2.1. The relative importance of risk factors

Three decision-makers, d, $d = 1, \ldots, D$, participated in the evaluation process: a sports journalist ($d = 1$), a football coach ($d = 2$), and a football scout ($d = 3$). Each of them evaluated the importance of the considered risk criteria based on predefined linguistic expressions. These linguistic expressions were designed as triangular fuzzy numbers (TFNs), distributed on a scale [0–1]. The linguistic expressions used are as follows:

- Equal importance (X1): (1, 1, 3)
- Slightly more important (X2): (1, 3, 5)
- Moderately more important (X3): (3, 5, 7)
- Strongly more important (X4): (5, 7, 9)
- Extremely more important (X5): (7, 9, 9)

It is worth noting that expert opinions were obtained from the aforementioned decision-makers and may differ from those of decision-makers within the clubs. These changes can have an impact on the final weighting of the criteria. Each club/expert team should conduct its own assessment.

To determine the overall weights of the criteria, the FAHP approach was used. This process ensures that the subjective evaluations of decision-makers are methodically integrated, yielding a consistent and credible weight distribution for the criteria.

2.2. Modeling of risk factor values

To assess the values of risk factors, different data sources and approaches were used, depending on the nature of each criterion. For the first criterion, player's market value (Severity – S), data were sourced from transfermarkt.co.uk, a well-established platform for estimating player market values. The rationale for adopting this platform stems from its extensive database, which brings together input from experts, scouts, and market analysts to provide realistic and commonly acknowledged appraisals of football players.

The other two criteria, frequency of club changes or a player's injury history (Occurrence – O) and adaptability to diverse tactics and playing styles (Detection – D), were assessed through the decision-makers' evaluation. These assessments were necessarily subjective, relying on the evaluators' knowledge, experience, and viewpoints.

The fuzziness in these judgments is a result of the complexity and ambiguity inherent in these variables. For example, the frequency of club changes or a player's injury history is difficult to quantify effectively. Club changes can occur for various reasons, including financial considerations or management decisions that are unrelated to the player's performance. Furthermore, injuries can range from mild to serious and have varying consequences for a player's career and adaptability.

Similarly, determining a player's adaptability to different tactics and playing styles adds to the difficulty. Adaptability is a multidimensional characteristic that is influenced by factors such as playing experience, tactical flexibility, and level of competition. Precise evaluation is difficult, and subjective evaluations might differ greatly among evaluators.

To solve these issues, fuzzy logic was used to simulate these two issues. Fuzzy sets can express imprecision and different levels of uncertainty in the data, allowing for more flexible and realistic modeling approaches. By using fuzzy values, the inherent uncertainties and subjectivities in the assessment are better captured, providing a robust basis for subsequent analyses. The linguistic expressions used, modeled using TFNs, are presented in Table 1.

Table 1
The linguistic expressions used for risk factors O and D

Linguistic Expression	TFN
Extremely low value (V1)	(1, 1, 3)
Very low value (V2)	(1, 2, 3)
Low value (V3)	(2, 3, 4)
Moderate value (V4)	(4, 5, 6)
High value (V5)	(6, 7, 8)
Very high value (V6)	(7, 8, 9)
Extremely high value (V7)	(7, 10, 10)

A scale of 1 to 10 was used, with overlapping fuzzy numbers to ensure consistency with the conventional FMEA framework.

The next section explains the steps of the proposed model.

3. The Proposed Algorithm

The proposed algorithm consists of two phases. In the first phase, the criteria weights are determined using the FAHP method, while in the second phase, the potential transfers are ranked using the FRADAR method.

Phase 1:

Step 1. Constructing the fuzzy pair-wise comparison matrix:

$$\left[\widetilde{W}_{kk'}\right]_{K\times K}$$

where $k,\ k' = 1,\ \ldots,\ K;\ k \neq k'$.

Step 2. Checking the consistency of the assessments made by each decision-maker in Step 1.

To examine the consistency of the evaluations, it is necessary to defuzzify the fuzzy values. The defuzzification process was carried out using the approach developed by Kahraman et al. [19]:

$$\left[\widetilde{W}_{kk'}\right]_{K\times K} = defuzzified\left[\widetilde{W}_{kk'}\right]_{K\times K}$$

where $k,\ k' = 1,\ \ldots,\ K;\ k \neq k'$.

Afterward, the consistency check is performed using the eigenvector method [20].

If $CI \leq 0.1$, the evaluations provided by the decision-makers are considered consistent.

Step 3. The further application of the FAHP method was carried out using fuzzy algebra rules, ultimately yielding the criteria weights at the level of each decision-maker, $\widetilde{\omega}_k^d$.

Step 4. The aggregation of criteria weights was performed using the fuzzy arithmetic mean operator, $\widetilde{\omega}_k$.

It is important to emphasize that the first two criteria are cost related, while the third criterion is benefit related.

Phase 2:

Step 5. A fuzzy decision matrix, $\left[\widetilde{M}_{ik}\right]_{I\times K}$, is created based on the assessments of the decision-makers and data from the website transfermarkt.co.uk. The decision-makers made their assessments by consensus in an online discussion.

The calculations with fuzzy numbers were performed using the basic fuzzy algebra rules [21, 22].

Step 6. The fuzzy maximum proportion matrix, $\widetilde{\alpha}$:

$$[\widetilde{\alpha}_{ik}]_{I\times K}$$

For the benefit-related criteria,

$$\widetilde{\alpha}_{ik}=\frac{\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}}{\left(\left(\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}\right)+\left(\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}\right)\right)}$$

For the cost-related criteria,

$$\widetilde{\alpha}_{ik}=\frac{\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}}{\left(\left(\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}\right)+\left(\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}\right)\right)}$$

Step 7. The fuzzy minimum proportion matrix, $\widetilde{\beta}$:

$$\left[\widetilde{\beta}_{ik}\right]_{I\times K}$$

For the benefit-related criteria,

$$\widetilde{\beta}_{ik}=\frac{\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}}{\left(\left(\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}\right)+\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}\right)}$$

For the cost-related criteria,

$$\widetilde{\beta}_{ik}=\frac{\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}}{\left(\left(\frac{\max_{i}\widetilde{M}_{ik}}{\widetilde{M}_{ik}}\right)+\frac{\widetilde{M}_{ik}}{\min_{i}\widetilde{M}_{ik}}\right)}$$

Step 8. The fuzzy empty range matrix:

$$[E_{ik}]_{I\times K}$$

where

$$E_{ik}=|\alpha_{ik}-\beta_{ik}|$$

where α_{ik} is the defuzzified value of $\widetilde{\alpha}_{ik}$ and β_{ik} the defuzzified value of $\widetilde{\beta}_{ik}$ [19].

Step 9. The fuzzy relative relations matrix:

$$\left[\widetilde{RR}_{ik}\right]_{I\times K}$$

where

$$\widetilde{RR}_{ik}=\frac{\widetilde{\alpha}_{ik}}{\widetilde{\beta}_{ik}+E_{ik}}$$

Step 10. The fuzzy weighted relative relations matrix:

$$\left[\widetilde{WRR}_{ik}\right]_{I\times K}$$

where

$$\widetilde{WRR}_{ik}=\widetilde{RR}_{ik}\cdot\widetilde{\omega}_{k}$$

Step 11. The aggregated ranking index, RI_i:

$$RI_i=\frac{\min\sum_{k=1}^{k} defuzz\,\widetilde{WRR}_i}{\sum_{k=1}^{k} defuzz\,\widetilde{WRR}_i}$$

In this case, the same defuzzification procedure was applied.

The ranking of the evaluated football player transfers is established, with the highest RI_i value indicating the player to be prioritized for acquisition. The same logic applies in reverse. To understand the proposed model more clearly, its key elements are presented in Figure 1.

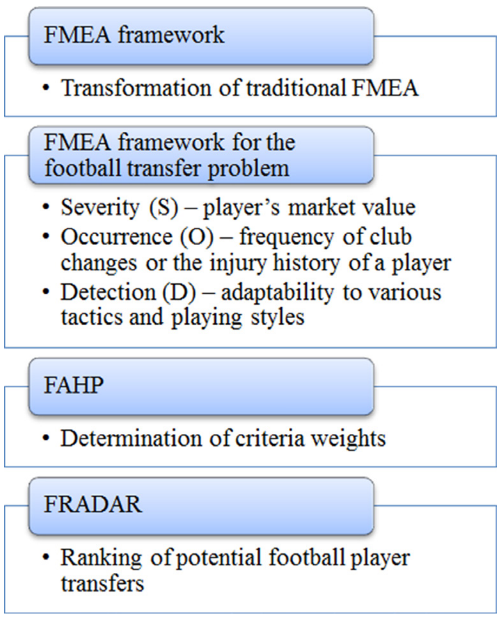
The following section demonstrates the application of the proposed algorithm through a case study based on the analysis of a random group of football players.

4. Case Study

The case study, in particular the illustrative example of the application of the proposed model, was conducted on a sample of five randomly selected football players. The author, in collaboration with the decision-makers, selected players from the top five European football leagues according to the Union of European Football Associations and their association club coefficients. These leagues are English, Spanish, Italian, German, and French. One player is selected from each league, all playing the central defender position. The players selected were of similar age, between 23 and 26 years old. The remaining parameters were determined randomly.

To safeguard privacy and respect individuals' rights to confidentiality, no player names or other personal information were shared in this study. While this study focuses on football player transfers, the data used is broad, such as player performance, injury history, or frequency of club changes, and does not reveal personal information or player identities. Furthermore, this approach aligns with ethical norms in sports research, which require that data be utilized for analytical and scientific purposes without violating individuals' rights

Figure 1
The proposed model



or using sensitive information without their consent.

As mentioned in Step 1 of the proposed algorithm, decision-makers expressed their estimates of the relative importance of the criteria. Meanwhile, Step 2 of the proposed algorithm was used to calculate the correlation coefficient, *CI*.

$$
\begin{array}{ccc}
d=1 & d=2 & d=3 \\
\begin{bmatrix} 1 & X3 & X4 \\ \square & 1 & X1 \\ \square & \square & 1 \end{bmatrix} &
\begin{bmatrix} 1 & X2 & X3 \\ \square & 1 & X1 \\ \square & \square & 1 \end{bmatrix} &
\begin{bmatrix} 1 & X2 & X4 \\ \square & 1 & X2 \\ \square & \square & 1 \end{bmatrix} \\
CI = 0.02 & CI = 0.06 & CI \approx 0
\end{array}
$$

By applying Step 3 of the proposed algorithm, the criteria weights at the level of each decision-maker were determined, $\widetilde{\omega}_k^d$:

$$
\begin{array}{cccc}
 & \widetilde{\omega}_1 & \widetilde{\omega}_2 & \widetilde{\omega}_3 \\
d=1 & (0.16,\ 0.68,\ 2.34) & (0.07,\ 0.24,\ 1,57) & (0.02,\ 0.08,\ 0.25) \\
d=2 & (0.09,\ 0.63,\ 3.43) & (0.06,\ 0.28,\ 2.20) & (0.02,\ 0.09,\ 0.38) \\
d=3 & (0.10,\ 0.61,\ 3.31) & (0.06,\ 0.32,\ 2.27) & (0.02,\ 0.07,\ 0.33)
\end{array}
$$

As described in Step 4 of the proposed algorithm, the decision-makers' assessments were aggregated using the arithmetic mean operator:

$$
\begin{aligned}
\widetilde{\omega}_1 &= (0.12,\ 0.64,\ 3.03) \\
\widetilde{\omega}_2 &= (0.06,\ 0.28,\ 2.01) \\
\widetilde{\omega}_3 &= (0.02,\ 0.08,\ 0.32)
\end{aligned}
$$

According to Step 5 of the proposed algorithm, the fuzzy decision matrix is established (Table 2):

The player's market value was taken from the website transfermarkt.co.uk and is given in millions of euros. The fuzzy values of the other two criteria were ed by the decision-makers through consensus based on predefined linguistic expressions.

To proceed to Steps 6 and 7 of the proposed algorithm, the minimum and maximum values of each alternative for every criterion must be determined. Since these values are actual predefined linguistic statements modeled using TFNs, the minimum and maximum values can be derived based on the given gradation.

An example of calculating the first element of the fuzzy maximum proportion matrix:

$$\widetilde{\alpha}_{11} = \frac{\frac{45}{12}}{\left(\frac{45}{45} + \frac{45}{12}\right)} = 0.79$$

Tables 3 and 4 present the fuzzy maximum proportion matrix and the fuzzy minimum proportion matrix, respectively.

According to Step 8 of the proposed algorithm, the values of the empty range matrix (Table 5) are calculated. To achieve this, we first need to defuzzify the values of the previous two matrices. The element of the empty range matrix is always a crisp and positive number. An example of calculating the first term of this matrix is as follows:

$$E_{11} = |0.79 - 0.21| = 0.58$$

In Step 9, the elements of the fuzzy relative relations matrix are calculated as shown in Table 6. An example of calculating an element of this matrix is as follows:

$$
\begin{aligned}
\widetilde{RR}_{13} &= \frac{\widetilde{\alpha}_{13}}{\widetilde{\beta}_{13} + E_{13}} \\
&= \frac{(0.25, 0.77, 2.22)}{(0.07, 0.23, 0.89) + (0.68, 0.68, 0.68)} \\
&= (0.16,\ 0.84,\ 2.95)
\end{aligned}
$$

Table 2
The fuzzy decision matrix

Player	S (k = 1)	O (k = 2)	D (k = 3)
i = 1	45	V3	V3
i = 2	12	V2	V4
i = 3	30	V2	V3
i = 4	20	V5	V4
i = 5	25	V2	V7

Table 3
The fuzzy maximum proportion matrix

Player	S (k = 1)	O (k = 2)	D (k = 3)
i = 1	(0.79, 0.79, 0.79)	(0.08, 0.39, 1.85)	(0.25, 0.77, 2.22)
i = 2	(0.21, 0.21, 0.21)	(0.03, 0.22, 1.29)	(0.21, 0.55, 1.15)
i = 3	(0.62, 0.62, 0.62)	(0.03, 0.22, 1.29)	(0.25, 0.77, 2.22)
i = 4	(0.43, 0.43, 0.43)	(0.21, 0.78, 2.91)	(0.21, 0.55, 1.15)
i = 5	(0.54, 0.54, 0.54)	(0.03, 0.22, 1.29)	(0.11, 0.23, 0.58)

Table 4
The fuzzy minimum proportion matrix

Player	S (k = 1)	O (k = 2)	D (k = 3)
i = 1	(0.21, 0.21, 0.21)	(0.19, 0.61, 1.85)	(0.07, 0.23, 0.89)
i = 2	(0.79, 0.79, 0.79)	(0.18, 0.78, 3.43)	(0.18, 0.45, 1.38)
i = 3	(0.38, 0.38, 0.38)	(0.18, 0.78, 3.43)	(0.07, 0.23, 0.89)
i = 4	(0.57, 0.57, 0.57)	(0.08, 0.22, 0.48)	(0.18, 0.45, 1.38)
i = 5	(0.46, 0.46, 0.46)	(0.18, 0.78, 3.43)	(0.27, 0.77, 2.04)

Table 5
The empty range matrix

Player	S (k = 1)	O (k = 2)	D (k = 3)
i = 1	0.58	0.11	0.68
i = 2	0.58	0.95	0.03
i = 3	0.24	0.95	0.68
i = 4	0.14	1.04	0.03
i = 5	0.08	0.95	0.72

Table 6
The fuzzy relative relations matrix

Player	S (k = 1)	O (k = 2)	D (k = 3)
i = 1	(1.00, 1.00, 1.00)	(0.04, 0.54, 6.17)	(0.16, 0.84, 2.95)
i = 2	(0.15, 0.15, 0.15)	(0.01, 0.13, 1.14)	(0.15, 1.14, 5.39)
i = 3	(1.00, 1.00, 1.00)	(0.01, 0.13, 1.14)	(0.16, 0.84, 2.95)
i = 4	(0.61, 0.61, 0.61)	(0.14, 0.62, 2.60)	(0.15, 1.14, 5.39)
i = 5	(1.00, 1.00, 1.00)	(0.01, 0.13, 1.14)	(0.04, 0.15, 0.59)

Table 7
Defuzzified values of $\widetilde{WRR}_i$

Player	S (k = 1)	O (k = 2)	D (k = 3)	Sum
i = 1	1.26	4.18	0.34	5.78
i = 2	0.19	0.78	0.61	1.58
i = 3	1.26	0.78	0.34	2.38
i = 4	0.77	1.80	0.61	3.17
i = 5	1.26	0.78	0.07	2.11

Table 8
Ranking of football players

Player	RI_i	Rank
i = 1	0.27	5
i = 2	1.00	1
i = 3	0.66	3
i = 4	0.50	4
i = 5	0.75	2

In Step 10, the values of the fuzzy weighted relative relations matrix are calculated. Since the values of this matrix are merely the product of the criterion weights and the values of the fuzzy relative relations matrix (Step 11, Table 6), the calculation procedure is not demonstrated. Instead, the final defuzzified values of $\widetilde{WRR}_i$ are provided (Table 7).

The considered alternatives, i.e., potential players, are ranked based on the aggregated ranking index. An example of calculating this value is as follows:

$$RI_1 = \frac{1.58}{5.78} = 0.27$$

Table 8 shows all values of the aggregated ranking index, as well as the ranking of the considered football players.

From Table 8, it can be concluded that the least risky option would be to recruit player i = 2. His low market value, along with a tendency not to frequently change clubs or be absent due to injuries, places him at the top of the priority list. Furthermore, according to the decision-makers, he can adapt relatively easily to different tactical variations and playing systems. When evaluated objectively, the proposed methodology provided a very logical result in this case.

In the event of unsuccessful negotiations, players should be contacted in the order presented. At the bottom of the ranking is player i = 1. A significantly higher cost compared to other candidates, along with relatively poor scores in the other two criteria, justifiably places him in last position.

5. Conclusion

The findings of the present study emphasize the need for a systematic approach to risk assessment in football player transfers. The model, which uses a combination of FAHP and FRADAR methods as well as the FMEA framework, allows for informed decision-making based on the assessment of key risk factors such as market value, frequency of club changes or injuries, and adaptability to different tactics and playing styles (e.g., coach changes). This technique reduces the financial and tactical risks involved with unsuccessful transfers, which is especially essential for clubs with restricted funds.

As demonstrated in the case study, the model successfully ranked potential transfers, taking into account the advantages and disadvantages of each candidate. Of course, the proposed model can be applied with certain variations and adjustments based on specific preferences.

Based on the results obtained, club managers can better allocate their resources and strategies, prioritizing players who represent the least risk to the long-term stability and success of the club. This methodology not only contributes to reducing risks but also optimizes the entire decision-making process in professional football, enabling more accurate analysis and better adaptation to different managerial needs.

One of the key advantages of the proposed model is its flexibility and adaptability to different contexts and the needs of football club management. In this way, it provides a useful mathematical tool to support decision-making. The decision, however, is always made by people, and such a tool serves only as an auxiliary means.

One significant shortcoming of the proposed approach is its reliance on the quality of accessible data, which can be incomplete or subjective. Furthermore, while the model promotes informed decision-making, its implementation may be complex, necessitating additional training for managers and analysts.

Future research directions could involve introducing additional risk factors, such as a player's mental stability, interpersonal relationships within the team, and others. Furthermore, future research could explore the use of different fuzzy numbers to enhance the precision and reliability of risk assessment. Finally, combining other MADM methods could be considered to adapt the solution to specific situations.

Ethical Statement

This study does not include any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Nikola Komatina: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

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