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Evaluating Tennis Player Performance Based on Biomechanical Variables Using Multi Criteria Decision Making Techniques

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Abstract: In tennis, choosing the right player can be extremely difficult because their performance in a match depends on many biomechanical criteria. Thus, this study aims to establish a framework to help coaches select the best tennis players based on a set of biomechanical parameters. Tennis involves specific strategies that require players to execute serves accurately and professionally to get more points. Consequently, there are biomechanical criteria that evaluate each player's performance. Multi-criteria decision-making (MCDM) techniques have provided optimal solutions to various problems. The methodology proposed in this study incorporates several decision-making techniques in two stages: the first involves calculating the weights of the selected criteria by combining triangular fuzzy numbers with the Analytical Hierarchy Process (AHP) technique. The second stage is to select the appropriate alternative using the TOPSIS technique, which focuses on the shortest geometric distance of the alternative from the positive ideal solution and the farthest geometric distance from the negative ideal solution. Additionally, the MOORA technique was applied, based on two attributes: beneficial value and non-beneficial value. The study's findings indicated that the first attempt (AT-1) was the best alternative in both techniques. Spearman correlation coefficient was employed to assess the relationship between the two techniques, and a sensitivity analysis was conducted based on the ranking results derived from both techniques.

Keywords: Tennis Player, Biomechanical Variables, MCDM Techniques, Triangular Fuzzy Numbers, AHP Technique, TOPSIS Technique, MOORA Technique.

Introduction

The world has witnessed significant scientific and technological progress in applying the best modern foundations in sports nowadays. These foundations have notably contributed to the advancement of sporting levels in many games and events, including tennis (Setyawan et al., 2024). This type of sport encompasses a set of skills that require in-depth study and analysis of its biomechanical aspects, which aids coaches in achieving accurate, objective results. These skills are essential in developing players' technical performance and identifying their strengths and weaknesses. For instance, the skill of a straight tennis serve necessitates timing, balance, muscle strength, arm speed, and high accuracy(Colomar et al., 2022) . Without the proper mechanics, all the effort will be wasted.

Each sport has a specific training strategy for players to ensure winning in matches(Caroline et al., 2021). Therefore, tennis players rely on a set of biomechanical factors that help them reach professional status. The process of training players on the court is important to prepare them to become professionals (Id & Muehlbauer, 2022). Therefore, coaches must monitor players during training to ensure they perform all professional movements in executing various strokes and serves to win matches.

Multi-criteria decision-making techniques have provided numerous solutions in various sectors, including sports (Yi et al., 2024). There are several biomechanical parameters that every player must consider. In this study, these parameters represent the criteria for evaluating a tennis player. Eleven attempts were made to evaluate a player's performance according to seven basic criteria. Triangular fuzzy numbers were combined with the AHP to calculate the weights of the criteria (Temesi et al., 2024). Meanwhile, TOPSIS and MOORA techniques were used to select the optimal alternative (Jassim Al-Shamary et al., 2022),(Yas & Zaidan, 2023). The best player is then selected based on their on-court performance according to specific criteria.

Study problem

Selecting the best player based on his performance is usually the most difficult challenge coaches' face. Several trials were conducted during on-court tennis training based on several selected criteria, listed in Table 1. The various criteria used to select the alternatives are described in the next section.

Biomechanical factors overview

Tennis is considered a major sport around the world. There is great interest from sports organizations in many countries to recruit professional players to ensure winning in international tournaments. Consequently, over the years, many players have achieved impressive results and set world records. Therefore, coaches have focused on developing outstanding players by evaluating them during training according to biomechanical factors used in player selection(Martin, 2018), as follows:

- **Ball height:** The distance between the vertical line connecting the ground and the height of the ball at the moment of hitting
- **Ball launch angle:** The angle between the line that connects the center of the ball before its launch and the imaginary horizontal line, where the angle represents the point of intersection of the two lines
- **Ball launch speed:** The ball's release speed was calculated using the formula: speed = (distance/time).
- **Trunk inclination angle:** The angle between the line extending from the hip joint upwards (the imaginary vertical line) and the line passing through the shoulder joint

- **Shoulder angle:** The shoulder angle was measured using several lines: the line from the wrist joint, passing through the elbow joint and to the shoulder joint, and the line from the shoulder joint to the hip joint.
- **Height of the center of mass:** The distance between the maximum flexion of the knees from the moment the ball is thrown with the opposite hand to the moment the ball is struck with the full extension of the body.
- **Peripheral velocity of the arm:** The peripheral velocity of the hitting arm was measured from the moment the arm began to swing and the elbow joint extended to distance the racket from the axis of rotation (shoulder) in order to increase the peripheral velocity of the racket and thus increase the launch velocity of the ball.

Table 1, shows a dataset obtained by conducting several attempts to evaluate a player's performance. The table includes eleven attempts made by the tennis player according to seven specific criteria.

Table 1. Serving performance based on the biomechanical variables of the tennis player

Attempts	Ball height	Ball launch angle	Ball launch speed	Trunk inclination angle	shoulder angle	Height of the center of mass	peripheral velocity of the arm
AT-1	3.30	3	39	16	168	0.26	8.44
AT-2	3.28	5	34	13	159	0.25	7.89
AT-3	3.13	3	39	12	165	0.33	9.03
AT-4	3.41	6	40	10	156	0.31	9.03
AT-5	3.39	5	36	9	154	0.25	8.01
AT-6	3.15	4	38	8	145	0.26	8.15
AT-7	3.18	4	37	7	148	0.29	8.42
AT-8	3.33	4	37	6	156	0.30	8.07
AT-9	3.42	4	38	11	155	0.31	8.3
AT-10	3.24	6	40	10	152	0.33	9.06
AT-11	3.26	7	37	10	150	0.30	8.49

Motivation

The paper's contribution is highlighted by solving the problem of the tradeoff between criteria, which is considered a fundamental focus in the selection and benchmarking process. However, MCDM techniques have provided solutions to the research problem. These techniques are mainly based on mathematical models. In the TOPSIS technique, alternatives are selected based on the closest geometric distance to the positive ideal solution and the longest geometric distance from the negative ideal solution. Whereas the alternatives in the MOORA technique are selected based on criteria such as the beneficial and non-beneficial types. On the other hand, calculating the weights of criteria has a significant impact on the process of selecting the expected best alternative instead of selecting the actual best alternative. The paper aims to select the best tennis player based on MCDM techniques, taking into account the degree of compatibility of these techniques with the selection rules.

Literary review

The significant focus on developing players' skills in many modern sports has contributed to raising the standards of play in numerous games and events, including tennis. According to various literature, tennis has strategies for evaluating players based on specific physical and biomechanical factors.

Franck Brocherie and Daniel Dinu, (Brocherie & Dinu, 2022) utilized inertial measurement units in a 3D on-court measurement system to analyze the biomechanics of tennis serves. Two professional tennis players, equipped with an inertial measurement unit (Xsens MVN suit), performed two attempts of five serves each. The players were monitored during the loading phase for center of gravity rotation, all joint angles (shoulder, elbow, knee), center of mass displacements, and rotational dynamics, while similar development was recorded for both female and male participants from the loading phase to the end phase. Player performance was evaluated from the loading phases to the end. The total, minimum, and maximum energy contributions were comparable for both players, with the coefficient of variation deemed acceptable between the two experiments. Therefore, the inertial measurement unit (IMU) serves as a suitable method for collecting and subsequently analyzing biomechanical data on tennis serves, providing tennis players with personalized feedback to enhance their motor skills and serve efficiency.

JIAN LI ,et al. (X. Zhang & Yang, 2023) used deep learning (DL) image processing technology to study the effect of tennis players' hitting power and angle. A convolutional neural network (CNN) algorithm based on camera video images was applied to the joint angles of tennis players when executing the serve from a biomechanical perspective. Gaussian mixture model (GMM), visual background extractor (VIBE), and optical flow (OF) were used for simulation and comparison. The study results show that the processing frame rate, hit-and-run similarity score of the proposed algorithm, based on camera video image and CNN, are much higher than those of GMM, VIBE, and OF.

Zhiqiang, Liang, et al. (Liang et al., 2023) An inertial measurement system, which relies on a combination of accelerometers, gyroscopes, and magnetometers, is used to identify and monitor tennis movements. This system is important for assessing the main biomechanical dynamics of the serve phases and events. In addition, the kinematic metrics contribute during the serve to analyze their impact on serve velocity. Eighteen tennis players were divided into two groups, equipped with inertial measuring devices, and evaluated for an extended serve according to their positions above or below the average serve speed of the sample. According to the results obtained, relevant biomechanical differences during transmission were identified. Thus, it highlighted the changes in joint angles and angular velocities between the two groups. These results provide valuable information for coaches and players to improve their serve efficiency.

André V. Brito, et al. (Brito et al., 2024) studied the biomechanical performance of the footwork serve (FUS) in female tennis players of different skill levels. 32 female tennis players were tested in the biomechanics laboratory to analyze their performance at three different levels. In this study, one-way analysis of variance (ANOVA) was applied to examine the differences in kinetic data between groups. Three-dimensional biomechanical data were collected for the lower extremities of female tennis players during the foot serve. The results demonstrated that the range of motion (ROM) of bilateral lower extremity joints resulted in significant differences in motor performance during the preparation and landing phases ($p < 0.05$). Therefore, joint range of motion and lower extremity stiffness significantly influence tennis players' performance in FUS training. Joint flexibility and lower extremity stiffness enhance performance during the preparation phase of FUS training.

Li, Zhuoyuan ,and Yin, Yitian, (Li & Yin, 2024) developed a player performance evaluation model based on the EWM-TOPSIS method to analyze players' momentum and its impact on their tennis performance. Various factors such as winning condition, distance, winners, and double faults were considered. The model differentially evaluates the winning motivations of servers and receivers and relies on an exponentially decreasing accumulation of evaluation indicators, similar to the momentum algorithm in deep learning. Players' performance scores at a given point, called the momentum score, were determined using the EWM-TOPSIS evaluation algorithm. In this study, a random match was selected to depict the momentum score for both sides to demonstrate the consistency of the momentum score and match conditions. The results of the study demonstrated that the relationship between momentum score and the increase or decrease in winning probability can be influenced by momentum score, which has a significant correlation with the volatility of winning probability.

Hraste, Mladen , et al. (Hraste & Jelaska, 2024) used the analytical hierarchy process (AHP)method to analyze the priorities of all-court tennis players. The study focused on investigating the priorities of tennis players on all courts in attack and defense. Eighteen criteria were selected to evaluate the overall performance of tennis players based on the expertise of seven tennis experts. The importance coefficient vectors assigned by each expert were calculated using the geometric mean method and used to form the decision matrix for the player on all courts. The arithmetic mean and standard deviation vectors were calculated for all criteria. The results showed that the top of the defensive hierarchy indicated the quality of defensive movement/tasks and the quality of the first serve and return, which are of high importance. While the quality of performance in long rallies is of medium to high importance. Therefore, the top of the offensive hierarchy indicated that playing with multiple styles and the quality of the first serve are of high importance. Conversely, the quality of initiative in rallies and the quality of the offensive forehand are of medium to high importance.

Materials and Methods

In this section, various decision support techniques are proposed for evaluating tennis player performance based on a set of biomechanical parameters. Subsequently, MCDM techniques combined with fuzzy logic, such as AHP, TOPSIS, and MOORA, are applied using a hybrid approach that integrates several decision support methods (Alazzawi, 2025),(Al-Azzawi et al., 2023),(Yas & Zaidan, 2023).

Materials

This study used an experimental dataset comprising eleven attempts made by a tennis player on the court based on seven selected criteria. These attempts represent alternatives based on a set of selected criteria that form the foundation for evaluating a tennis player's performance.

Tennis player Criteria

In this study, several biomechanical criteria for tennis players were considered for benchmarking. Each criterion was prioritized for a specific purpose and to achieve a specific goal within the decision matrix. Although conflicts between criteria may affect the importance of each criterion within the decision matrix (DM) (Almarashi et al., 2024). Thus, the criteria were evaluated using a reasonable balance to determine the priority and importance of each criterion based on their comparison.. Seven key criteria were identified that significantly influence tennis player performance, as ball height, ball launch angle, ball launch speed, trunk inclination angle, shoulder angle, height of the center of mass, and peripheral velocity of the arm, respectively. Figure 1, shown the various biomechanical variables performed be tennis players in the court.

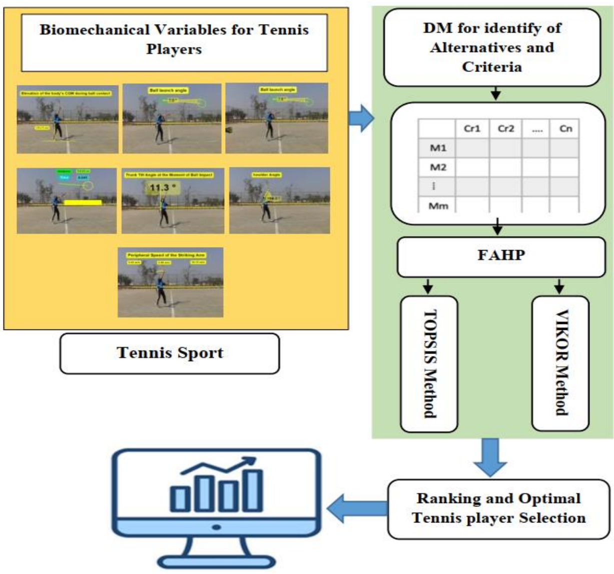

Figure 1. Taxonomy for selecting tennis player based on MCDM techniques.

Methods

In this section, several MCDM techniques used in this study for evaluation and selection are discussed (S. Zhang & Mao, 2021). In addition, the weights of the selected criteria are calculated.

Triangular fuzzy number

The fuzzy system proposed by L. Zadeh, called fuzzy set theory, is also called probability theory, and is based on the probability distribution of fuzzy variables (Zadeh, 1999) . The principle of fuzzy logic theory is based on crisp fuzzy values that can be determined for a specific variable. This theory has been widely accepted by researchers and applied in various disciplines to contribute to solving problems in various sectors, such as industry, education, and healthcare. Many methods and models based on fuzzy logic have been derived, such as the fuzzy triangular number approach (Yas et al., 2021). Three elements are the components of the triangular fuzzy number approach as:

$\tilde{\boldsymbol{a}} = \ (\boldsymbol{a}^{\boldsymbol{l}}, \boldsymbol{a}^{\boldsymbol{m}}, \boldsymbol{a}^{\boldsymbol{u}})$ defined a membership function as follows (Zhang, S. F., Liu, S. Y., & Zhai, 2011)

$$\text{Triangular Fuzzy Numbers} \quad \tilde{a} = \ (a^l, a^m, a^u) \tag{1}$$

$$\mu\ \tilde{a}\ (x) = \begin{cases} (x - a_l)\ /\ (a_m - \ a_l) & if\ a_l \le x \ \le \ a_m \\ (a_u - x)\ /\ (a_u - \ a_m) & if\ a_m \le x \ \le \ a_u \\ 0, & Otherwise. \end{cases}$$

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) method, based on the pairwise comparison principle, was used. The AHP method was integrated with the triangular fuzzy numbers approach to calculate the weights of the different criteria selected in this study. According to (Yas, Q. M., Ibrahim, D. S., & Mohammed, 2023) , the fuzzy number for pairwise comparisons is based on triangular fuzzy numbers, which take into account the interdependence of the criteria of the decision matrix . However, directly calculating fuzzy eigenvalues and fuzzy eigenvectors is very difficult in practice (Xiao et al., 2022). Therefore, a generated decision matrix (DM) that consists of m alternatives (eleven trials) and n criteria (seven criteria) can be defined, where the i-th alternative intersects with the j-th criterion (Zaidan et al., 2019). Figure 2 shows a flowchart of the Analytic Hierarchy Process (AHP) method (Saaty, 2001).

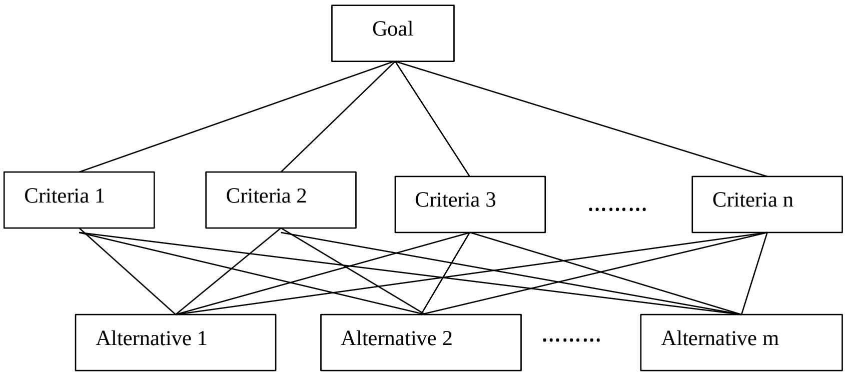

Figure 2. Analytical hierarchical process (AHP) method diagram.

According to T.Saaty, different metrics are proposed to compare the selected criteria based on experts' preferences (Saaty, 2012). These scales are defined in rational intervals from 1 to 9. According to this formulation of scales, they can be represented in linguistic terms and thus transformed into fuzzy triangular numbers. Therefore, fuzzy scales are considered effective methods to properly deal with this ambiguity. Table 2, shows the process of converting the values used in the decision matrix based on a five-point of Likert classifier for TFN scales.

Table 2. Likert classifier for TFN scales.

Description of scales	Triangular Fuzzy Number
Equal preference	(1,1,1)
Slight preference	(2,3,4)
Strong preference	(4,5,6)
Very strong preference	(6,7,8)
Excellent preference	(8,9,10)

Therefore, the FAHP approach was implemented using pairwise comparison, based on the preferences of decision-makers. The values of the linguistic decision matrix were changed to the triangular fuzzy numbers form. Thus, calculating criteria weights according to the FAHP approach, to be used as input values for the TOPSIS, MOORA, and other techniques later.

TOPSIS Technique

This technique is considered one of the best MCDM technologies according to it is characteristics (F. M. Jumaah, A. A. Zaidan, B. B. Zaidan, R. Bahbibi, M. Y. Qahtan, 2018),. According to the rules of this technique, which is based on selecting alternatives based on the closest geometric distance of the alternative to the positive ideal solution and the longest geometric distance from the negative ideal solution. Therefore, the closest geometric distance of the alternative to the positive ideal solution is used to choose the best alternative. Meanwhile, the farthest geometric distance of the alternative from the negative ideal solution is used to choose the worst alternative. In detail the steps of the TOPSIS method are discussed as follows:

- **Step 1-** Normalization of the decision matrix

  This step involves performing a comparison process between attributes by converting dimensional attributes into non-dimensional attributes.

$$r_{ij} = \boldsymbol{x_{ij}} / \sqrt{\sum_{i=1}^{m} \boldsymbol{x_{ij}^2}} \quad \textbf{(2)}$$

  The result of this step generates a new matrix R that can be described as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (3)$$

- **Step 2-** Weighted of normalized decision matrix

  This step included the set of criteria weights $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_n$, as in the decision matrix. Decision matrix values are calculated by multiplying each column in the decision matrix (R) by its associated weight (R) by its associated weight w_j, which should equal 1.
- **Step 3-** Determine the ideal solution and the negative solution

  This step included identifying the two alternatives A* (the ideal alternative) and, A^- (the negative ideal alternative) as follows:

$$A^* = \left\{ \left(\left(\max_i v_{ij} \middle| j \in J \right), \left(\min_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2, \ldots, m \right) \right\} \quad (4)$$

$$= \{ v_1^*, v_2^*, \ldots, v_j^*, \cdots v_n^* \} \quad (5)$$

$$A^- = \left\{ \left(\left(\min_i v_{ij} \middle| j \in J \right), \left(\max_i v_{ij} \middle| j \in J^- \right) \middle| i = 1,2, \ldots, m \right) \right\} \quad (6)$$

$$= \{ v_1^-, v_2^-, \ldots, v_j^-, \cdots v_n^- \} \quad (7)$$

where a subset of J is $\{i = 1,2, \ldots, m\}$, to be included the benefit attribute. Correspondingly, the values of J^- are the complementary set of J, or (J^c), which represent the cost attribute.

- **Step 4-**Calculate the separation measure based on the Euclidean distance

  This step involved calculating the ideal vector A* through the process of separating the alternatives according to the Euclidean distance for each alternative in V as follows:

  Where, $C_{i^*} = 1$ if and only if $(\mathrm{A_i} = \mathrm{A}^*)$, similarly, $C_{i^*} = 0$ if and only if $(\mathrm{A_i} = \mathrm{A}^-)$.

MOORA Technique

A multi-objective optimization technique based on ratio analysis was developed by Brauers and Zavadskas (Shahzadi, G., Luqman, A., & Ali Al-Shamiri, 2022). MOORA technique can be described in three main basic steps to be applied in the real world. Two main features are described: A beneficial feature to be as a maximum value, while a non-beneficial feature to be as a minimum value in this technique. A decision matrix is generated, where *m* denotes the alternatives (number of concentrations) while *n* is the number of criteria for these alternatives. The decision matrix includes the value *xij*, should be within (0 and 1) to calculate the normalization values. In this technique, the normalization values of the alternatives as *ith* ,while the *jth* are represented for the criteria, to be the positive value of (beneficial feature) and the negative value of (nonbeneficial feature) as follows:

- **Step1**- Calculating normalized decision matrix

$$x_{ij}^{*} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^{2}}, (i = 1, 2, ..., m; j = 1, 2, ..., n) \tag{8}$$

- **Step2**: Estimating assessment values

$$y_i = \sum_{i=1}^{m} w_j x_{ij} - \sum_{j=1}^{n} w_j x_{ij} \tag{9}$$

- **Step 3-** Calculating the Rank of alternatives

  Calculating the maximum value of the variable *yi* which represents the maximum priority and first rank, the second largest value of *yi* represents the second priority and second rank, and so on.

Comparative analysis

In this section, an analytical comparison using Spearman's rank correlation coefficient (rs) is applied to verify the values of the results obtained for both techniques (Ali & Al-Hameed, 2022). This method is considered unique for comparing the ranks of the alternatives applied in this study. Typically, rs measures the similarity between two sets of evaluations of the techniques applied in our study. Spearman's method is based on a rule for measuring similarity values between ranks, which typically range between -1 and 1 (Yu & Hutson, 2024).

Results and Discussions

In this section, the results are discussed in several stages according to the proposed methodology, employing a multi-criteria decision-making method (MCDM) technique. In the first stage, the weights of the selected criteria are calculated using FAHP. In the second stage, the ranks for all attempts made by a tennis player on the court are calculated using two MCDM techniques. Additionally, an analytical comparison of each rank based on the two techniques is performed using Spearman's correlation coefficient (SCC). Consequently, these results are verified through a sensitivity analysis.

Results of criteria weights

The results of the criteria weights are obtained by integrating fuzzy logic with the AHP method. The weights were calculated based on the pair-wise concept while checking the consistency between the values according to the rules of the AHP technique. These results were obtained according to the preferences of six experts. Table 3, shows the weights of various criteria based on experts' opinions.

Table 3. Results of criteria weights using FAHP approach.

	Ball Height	**Ball launch Angle**	**Ball launch Speed**	**Trunk Inclination Angle**	**Shoulder Angle**	**Height of the Center of mass**	**Peripheral Velocity of the Arm**
Exp-1	0.320	0.045	0.190	0.138	0.231	0.076	0.045
Exp-2	0.305	0.071	0.187	0.144	0.212	0.081	0.028
Exp-3	0.342	0.084	0.203	0.094	0.230	0.047	0.081
Exp-4	0.312	0.268	0.118	0.072	0.204	0.026	0.072
Exp-5	0.282	0.134	0.203	0.085	0.251	0.047	0.073
Exp-6	0.278	0.216	0.121	0.160	0.151	0.073	0.050

TOPSIS technique ranking for alternatives

The TOPSIS technique results identified alternative 1, with the first attempt being the best alternative for a tennis player. The worst alternative was recorded at attempt 7. The remaining alternatives were ranked as shown in Table 4.

Table 4. Results of TOPSIS technique for alternatives.

Alternatives	EXP-1		EXP-2		EXP-3		EXP-4		EXP-5		EXP-6		Rank
	S+	S-	S+	S-	S+	S-	S+	S-	S+	S-	S+	S-	
AT-1	12.6435	3.3911	11.6284	2.4216	12.6072	3.3082	11.0476	1.8080	13.6695	4.3719	8.2881	1.5897	1
AT-2	11.2357	1.9819	10.3230	1.1231	11.2035	1.9002	9.8483	0.9813	12.1597	2.8773	7.3473	2.2434	3
AT-3	12.1793	2.8692	11.1976	1.9006	12.1580	2.8409	10.6489	1.3898	13.1833	3.8736	7.9539	1.5824	2
AT-4	10.9245	1.6524	10.0522	0.9155	10.9179	1.6892	9.5306	0.6664	11.8266	2.5559	7.1319	2.3851	4
AT-5	10.5635	1.2401	9.7092	0.4345	10.5460	1.2271	9.2441	0.6685	11.4381	2.1321	6.8923	2.5698	9
AT-6	9.4194	0.4545	8.6687	0.8953	9.4163	0.5999	8.2066	1.2141	10.1971	0.9894	6.1420	3.3079	8
AT-7	9.7821	0.5151	8.9969	0.5252	9.7734	0.5982	8.5405	0.9378	10.5916	1.3069	6.3787	3.0595	11
AT-8	10.8548	1.5210	9.9781	0.6561	10.8393	1.5217	9.4940	0.5654	11.7543	2.4441	7.0787	2.3569	6
AT-9	10.7435	1.4549	9.8805	0.7087	10.7291	1.4476	9.3829	0.4842	11.6289	2.3276	7.0130	2.4686	7
AT-10	10.3841	1.1808	9.5583	0.7133	10.3813	1.2513	9.0491	0.7057	11.2408	2.0062	6.7796	2.7365	5
AT-11	10.0483	0.7876	9.2419	0.4818	10.0373	0.8275	8.7926	1.0719	10.8808	1.6246	6.5719	2.9662	10

MOORA technique ranking for alternatives

The results of the MOORA technique determined alternative 1, where the first attempt was the best alternative, as a tennis player's performance. The worst alternative was recorded at attempt 7. The remaining alternatives were ranked as shown in Table 5.

Table 5. Results of MOORA technique for alternatives.

Alternatives	Exp-1		Exp-2		Exp-3		Exp-4		Exp-5		Exp-6	
	yi	RANK	yi	RANK	yi	RANK	yi	RANK	yi	RANK	yi	RANK
AT-1	1.2614	1	1.2210	1	1.1988	1	0.9997	1	1.3261	1	0.9270	1
AT-2	1.1431	3	1.1103	3	1.0986	4	0.9689	5	1.2336	5	0.8724	2
AT-3	1.1997	2	1.1582	2	1.1506	2	0.9545	6	1.2764	2	0.8560	6
AT-4	1.1386	4	1.1100	4	1.1104	3	0.9871	2	1.2543	3	0.8686	3
AT-5	1.0812	8	1.0488	8	1.0524	8	0.9253	7	1.1891	8	0.8064	8
AT-6	1.0457	10	1.0131	10	1.0181	10	0.8668	10	1.1429	10	0.7570	9
AT-7	1.0367	11	1.0028	11	1.0115	11	0.8652	11	1.1390	11	0.7439	11
AT-8	1.0616	9	1.0234	9	1.0410	9	0.8920	9	1.1743	9	0.7531	10
AT-9	1.1180	6	1.0832	6	1.0781	6	0.9171	8	1.2083	7	0.8177	7
AT-10	1.1249	5	1.0978	5	1.0977	5	0.9764	4	1.2380	4	0.8613	5
AT-11	1.0940	7	1.0704	7	1.0710	7	0.9851	3	1.2162	6	0.8654	4

According to the results obtained, the two techniques used were completely identical in selecting the best and worst cases, regardless of the other cases. This alignment resulted from the weighting of the criteria, which significantly impacted the final results.

In other words, the experts' preferences were fairly close in determining the superiority of each criterion over the other, supporting the view that group opinions are superior to individual opinions. Therefore, based on the results, attempt 1 is considered the best alternative for the specific study problem [30]. Therefore, it is recommended that coaches take these results into account when evaluating or selecting any tennis players. Figure 3 shows the different classifications according to the three MCDM techniques applied.

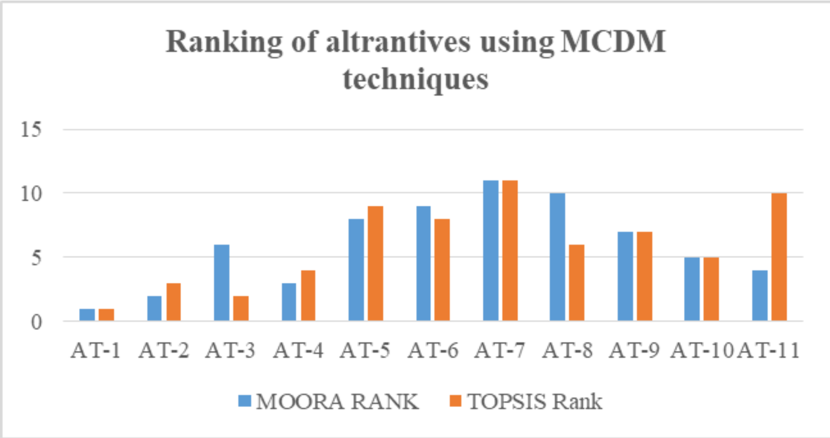

Figure 3. Ranking of Alternatives using MCDM techniques.

On the other hand, an analytical comparison used the Spearman correlation coefficient for the products collected from the application of FAHP-based MCDM techniques. The Spearman rank correlation coefficient (SCC) was calculated to assess the consistency between the rankings produced by the different MCDM techniques. The results revealed high positive correlations (ranging from 0.90 to 1.00), particularly between TOPSIS and MOORA methods, indicating strong agreement in ranking tennis player performance. According to the SCC rules the values obtained in the table range from 0.9 to 1.0 using the *rs* factor. Whereas, the values of the MCDM technique when compared to itself were recorded at a value of 1. See the table 6, shows the comparison between the TOPSIS and MOORA techniques.

Figure 4 shows that the results obtained from MOORA and TOPSIS match extremely. As is known, the different values of the criteria weights greatly affected the values of the results by using several techniques. Therefore, when the values of the criteria change, there is a high probability that the order of the alternatives will be changed.

Table 6. Spearman's rank correlation coefficient (SCC)

	TOPSIS	MOORA
TOPSIS	1	0.93
MOORA		1

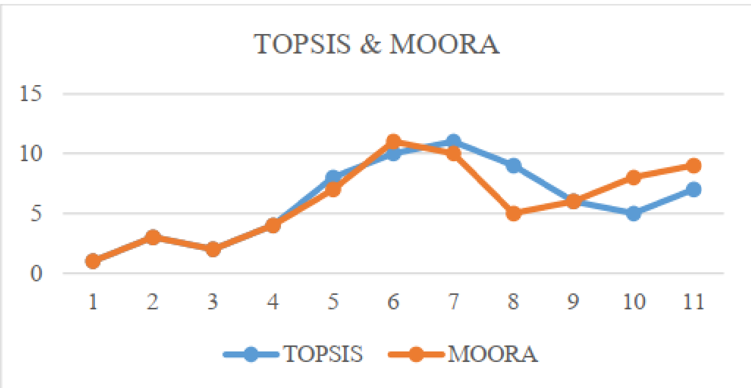

Figure 4. Comparison TOPSIS and MOORA results.

Conclusion

In the last decade, tennis has become one of the most popular Olympic sports worldwide. Various Olympic tournaments are held annually in many countries. Tennis matches are typically held outdoors, requiring players to perform at their best to win a match. However, evaluating a player's performance poses a challenge for coaches when selecting the right player based on several biomechanical criteria. In this study, several decision-making techniques combined with fuzzy logic were used. The Fuzzy Analytical Hierarchy Process (FHAP) was used to calculate the weights of the selected criteria. Seven basic biomechanical parameters were selected to evaluate tennis player performance. Two techniques were applied to select the optimal alternative as TOPSIS and MOORA. The results showed that the best alternative was the first attempt (AT-1) using both techniques. The correlation between the values of the two techniques was calculated using Spearman's Correlation Coefficient. In addition, five scenarios were used for sensitivity analysis of the ranking results of both techniques. Future work could apply more decision-making techniques to other cases, yielding impressive results.

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