



## Using artificial neural networks to assign soccer players by physical and motor abilities

*Uso de redes neuronales artificiales para asignar jugadores de fútbol según habilidades físicas y motoras*

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### Abstract

**Introduction:** The introduction of analytics tools in sports indicates that artificial neural networks can be one of the intelligent approaches to process complex data and identify patterns that help players move according to their most suitable positions.

**Objective:** The purpose of this research is to investigate the possibility of using artificial neural networks to determine the physical and motor abilities of football players and determine their suitable playing positions based on exact quantitative indicators.

**Method:** The study sample consists of 45 youth players aged (15–16) years from the Espanyol Football Academy in Baghdad. The results are analyzed using a multilayer perceptron (MLP) artificial neural network model to identify the relationships between physical variables and playing positions.

**Results:** The Pearson correlation analysis reveals statistically significant relationships between physical and motor abilities and the players' actual playing positions ( $p < 0.05$ ). In addition, the artificial neural network (MLP) model demonstrated the ability to assign players to different playing positions based on the relative weights of the variables. Speed, endurance, and explosive power were identified as the most influential factors in determining offensive positions, whereas flexibility and visual–motor coordination played a significant role in determining defensive positions and goalkeeping. The model achieved a classification accuracy exceeding 85%.

**Discussion:** The artificial neural network model demonstrates a high capacity to exploit correlational relationships and transform them from conventional statistical associations into accurate predictive patterns. This enables the model to guide players toward the most suitable playing positions based on their physical and motor characteristics.

**Conclusions:** The findings of the study confirm the feasibility of adopting artificial neural networks as an intelligent tool for sports performance analysis and for guiding youth players toward the playing positions most suited to their physical and motor abilities.

### Keywords

Artificial neural networks; football; physical abilities; intelligent guidance; playing positions.

### Resumen

**Introducción:** Con el desarrollo de las herramientas de análisis deportivo, las redes neuronales artificiales han surgido como uno de los enfoques inteligentes capaces de procesar datos complejos e identificar patrones que ayudan a orientar a los jugadores hacia las posiciones más adecuadas según sus habilidades.

**Objetivo:** Esta investigación tiene como objetivo explorar la viabilidad de emplear redes neuronales artificiales para analizar las capacidades físicas y motrices de los futbolistas y determinar sus posiciones óptimas de juego basándose en indicadores cuantitativos precisos.

**Método:** La muestra del estudio estuvo compuesta por 45 jugadores juveniles de entre 15 y 16 años de la Academia de Fútbol Espanyol de Bagdad. Los resultados se analizaron utilizando un modelo de red neuronal artificial de perceptrón multicapa (MLP) para identificar las relaciones entre las variables físicas y las posiciones de juego.

**Resultados:** El análisis de correlación de Pearson reveló relaciones estadísticamente significativas entre las capacidades físicas y motrices y las posiciones reales de juego de los futbolistas ( $p < 0,05$ ). Además, el modelo de red neuronal artificial (MLP) demostró la capacidad de asignar a los jugadores a diferentes posiciones de juego en función de los pesos relativos de las variables. La velocidad, la resistencia y la potencia explosiva se identificaron como los factores más influyentes para determinar las posiciones ofensivas, mientras que la flexibilidad y la coordinación visomotora desempeñaron un papel significativo en la determinación de las posiciones defensivas y la portería. El modelo alcanzó una precisión de clasificación superior al 85 %.

**Discusión:** El modelo de red neuronal artificial demostró una alta capacidad para aprovechar las relaciones correlacionales y transformarlas de asociaciones estadísticas convencionales en patrones predictivos precisos. Esto permitió al modelo orientar a los jugadores hacia las posiciones de juego más adecuadas en función de sus características físicas y motrices.

### Palabras clave

Redes neuronales artificiales; fútbol; habilidades físicas; guía inteligente; posiciones de juego.

## Introduction

In general, sport, and especially football, is undergoing a major transformation in training, technique, tactics, due to the growing developments of artificial intelligence technologies and big data analysis. Due to the change, coach's staff and trainers must rely on high-end scientific tools which help in measuring and analyzing sports performance accurately through which was not possible through regular means. As a result of this development, judging the player and assigning him to a position is not only judged based on the eyes. It is increasingly evident that we must rely on accurate data to assess that. It soon combines the physical, motor and technical aspect. (Watanabe, 2021).

One of the most vital football decisions is placing players in the best position on the field, which influences the success of the team. The process does not depend only on technical skills, but it does rely on physical abilities as well as motor characteristics and neuromuscular responsiveness that vary a lot depending on the template playing position. Football forwards must be quick and explosive while players in the defensive positions ought to be more flexible and possess good eye-foot coordination as well as tactical decision-making ability (Gómez-Carmona, 2018; de Souza, 2020). If you do not take these differences into account, players will be misallocated to positions where they do not fit and this will impact the overall performance of the team negatively.

With this complexity of player assessment, it is necessary to introduce some artificial intelligence techniques, especially artificial neural networks (ANN), which emerged as a powerful tool to assess complex sports data. Neural networks stand out due to their capacity to learn from data, identify patterns not visible to the naked eye, and address nonlinear relationships among multifaceted variables (Kelly, 2022).

Artificial neural networks represent a model inspired by the functioning of the human brain, as they consist of multiple layers of nodes (artificial neurons) that transmit data and perform advanced mathematical operations to generate accurate outputs. The introduction of the backpropagation algorithm has significantly improved neural network performance by iteratively adjusting weights and gradually minimizing error (Fang, 2021). Owing to this algorithm, neural networks have been able to learn efficiently from large and diverse datasets, leading to their application across various fields, including sports, for performance analysis, injury prediction, and the optimization of training programs (Dindorf, 2022).

Despite the wide range of applications of artificial neural networks, their use in guiding players according to their physical and motor abilities across playing positions remains an emerging field, with a clear research gap—particularly during the developmental and youth stages. Such scientifically grounded guidance, based on artificial intelligence models, not only assists in identifying the optimal playing position but also contributes to injury reduction, Improving overall performance, and the optimal utilization of human sports resources (Li, 2023; Skoki, 2025).

This study is based on the collection and analysis of quantitative data derived from objective field-based tests, including assessments of speed, explosive power, aerobic endurance, agility, flexibility, and eye-foot coordination. These data are used to train artificial neural network models, which learn the underlying patterns within the dataset and analyze the complex relationships between physical and motor abilities and the requirements of different playing positions. Consequently, these models serve as advanced decision-support tools for coaches, enabling more accurate and objective decision-making, independent of personal judgment or intuition (Islam, 2024).

The aim of this research is to develop an intelligent model using artificial neural networks based on precise physical and motor data of youth football players, in order to guide them toward playing positions that best match their abilities. It helps enhance the athlete's overall performance and efficiency by minimizing technical mistakes in position. The present work represents an intersection of data science, sports coaching science, and performance physiology, and constitutes a significant contribution to strengthening the integration of artificial intelligence within modern sports applications.

### Research Problem

Coaches often rely on personal experience and subjective observation when determining playing positions, which may lead to errors in player positioning. Consequently, the importance of utilizing artificial



neural networks has emerged as an analytical tool capable of accurately linking players' physical and motor abilities with the playing positions most suitable for them in a scientifically grounded manner.

### **Research Objectives**

1. To develop an artificial neural network model based on players' physical and motor abilities.
2. To determine the accuracy level of assigning players to playing positions using artificial neural networks.
3. To examine the nature of the correlational relationship between neural network outputs and the accuracy of player positioning.
4. To compare the accuracy of player positioning using artificial neural networks with traditional coach-based positioning methods.

### **Methodology**

This study adopted a quantitative approach with an exploratory and correlational design, aiming to examine the feasibility of employing artificial neural networks as an intelligent tool for guiding football players toward the most suitable playing positions based on their physical and motor abilities. This approach has proven to be effective, as supported by previous studies in the field of artificial intelligence applications in sports.

The study sample consisted of 45 male youth players aged between (15-16) years, all of whom were registered at the Espanyol Football Academy in Baghdad. The sample was selected on the basis of purposive sampling to reflect the targeted population of youth players receiving training. This approach is deemed suitable for research that needs specific characteristics from participants.

### **Participants**

The study included a sample of 45 healthy youth players who regularly trained at the academy. Approval from the players' parents or legal guardians and the academy administration, in accordance with the ethical standards of scientific research, was obtained prior to data collection.

### **Procedures**

The study was completed in three main parts. To start, the players completed physical and motor tests of music speed, endurance, flexibility, strength, and agility. According to Sannicandro (2017), the measurement of these components is recommended for football players.

Artificial neural network model of the Feedfor-ward Neural Net (FNN) type after data collection of data are entered. According to the recommendations for the development of machine learning models in the field of sports, the model has been created using the Python programming language and libraries such as TensorFlow and Keras.

The players' data and actual position classifications were used to train the model next. The results were tested against those actual playing positions in which they played the match to verify whether the outputs were correct or not. This stage is seen as crucial to ensure valid and reliable results.

#### *Tests Used*

##### First: Physical Tests

1. Speed (s / 30 m) {Cormier, 2024}:

Objective: The aim is to evaluate top speed in a running classification.

Procedure: The athlete will run 30 meters, from a standing start, with the time being recorded in seconds.

2. Explosive Leg Power (Vertical Jump) {Kennedy, 2021}:

Objective: To measure the explosive strength of legs.



Procedure: The athlete performs a vertical jump and the height of the jump is recorded in centimeters.

### 3. Aerobic Endurance (Cooper Test) {Isoniemi, 2022}:

Objective: Measurement of Cardio Respiratory Fitness

Procedure: The subject will run continuously for 12 minutes, and the total distance covered in meters will be measured.

#### Second: Motor Tests

#### 1. Flexibility (Sit and Bending Test) {Nuzzo, 2024}:

Objective: To measure flexibility of the lower back and hamstring muscles.

Procedure: The player sits and bends forward, and the reach distance is recorded in centimeters.

#### 2. Eye-Foot Coordination {Armando, 2020}:

Objective: To assess the ability to coordinate visual input with leg movement.

Procedure: Performed by kicking a ball toward small designated targets or passing through narrow pathways, with scoring out of 10 points.

#### Third: Agility {Papla, 2022}:

Objective: To assess the rate of direction change.

Procedure: The player runs through zigzags and the time taken is measured.

## Data Analysis

SPSS and Python were utilized to analyze the data. A set of descriptive statistics was used to extract indicators of physical fitness, whilst the accuracy metrics and the confusion matrix were used to evaluate the performance of the neural network. Furthermore, Pearson correlation tests were also performed between physical abilities and playing position recommendation model outputs.

## Results

First: In the initial step of the study, a descriptive statistical analysis was conducted for the research sample, which consisted of 45 youth players, with the aim of describing their general characteristics and determining the degree of homogeneity among them. Arithmetic means, standard deviations, and maximum and minimum values were calculated for variables such as age, height, weight, and training age, in addition to the results recorded in the physical and motor tests.

Sample homogeneity was also verified using the skewness coefficient, which is necessary to ensure that differences among players do not affect the results of the statistical analysis or the accuracy of the predictive model in later stages. This analysis helps determine the extent to which the sample participants are similar in their basic characteristics, thereby enhancing the reliability of the results and preventing bias in directing players to playing positions, as shown in Tables (1) and (2).

Table 1. Analysis of sample homogeneity in terms of basic characteristics (age, Training age, height, weight)

Variable	Unit of Measurement	Mean	Standard Deviation	Skewness Coefficient	homogeneity
Age	Year	15.5	0.51	- 0.04	homogeneity
Training age	Year	1.98	0.74	0.027	homogeneity
Height	Cm	165.4	4.90	0.17	homogeneity
weight	Kg	59.6	4.57	-0.18	homogeneity

Result: The sample is homogeneous in terms of age, height, and weight, according to the skewness coefficient between  $\pm 1$ .

Table 2. Descriptive statistics of the physical and motor characteristics of the research sample

Tests	Mean	SD	Min	Max
Speed (30 m, sec)	4.82	0.20	4.30	5.23
Flexibility (cm)	15.47	0.74	13.48	17.09
Aerobic endurance (m, Cooper)	1734	107	1570	1962



Vertical jump (cm)	22.4	3.32	16.00	31.60
Explosive leg strength (cm)	44.6	5.59	32.70	54.40
Agility (sec)	7.24	1.46	5.00	9.00

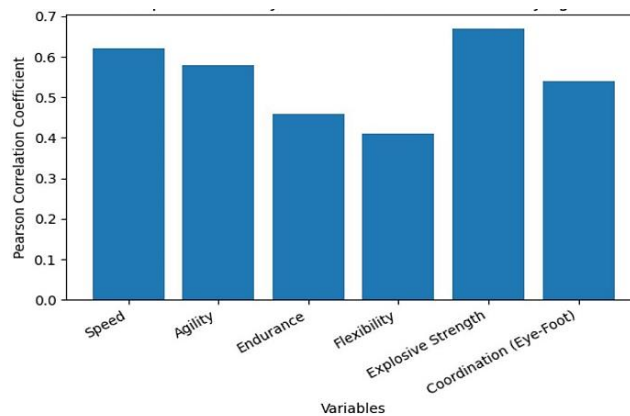
## Second: Correlational Analysis (Pearson) Between Abilities and Playing Positions

After describing the sample, (Pearson's correlation coefficient) was used to analyze the relationship between the results of the physical and motor tests on one hand, and the playing positions actually occupied by the players on the other hand (attack, midfield, defense, goalkeeper). This type of analysis helps identify the variables that have the greatest influence on determining the most suitable playing position for a player, as shown in Table (3) and figure (1).

Table 3. Relationship between physical and motor abilities and playing positions

Variable	Pearson's correlation coefficient	Statistical significance (p)
Speed	0.62	0.001
Agility	0.58	0.003
Endurance	0.46	0.012
Flexibility	0.41	0.021
Explosive strength	0.67	0.000
Coordination (eye-foot)	0.54	0.006

Figure 1. Show the relationship between physical abilities and playing positions.



It is observed from Table (3) that the results showed a positive and statistically significant Pearson correlation between physical and motor abilities and the accuracy of assigning players to playing positions. The correlation coefficients ranged between 0.41 and 0.67, indicating that these abilities are important indicators that can be reliably used to guide players accurately, especially when integrated into artificial neural network models. This analysis enabled the researcher to identify the most important variables for building the intelligent model in the third application.

## Third: Development of the Artificial Neural Network (ANN) Model

Operational Steps of the Artificial Neural Network:

1. Inputting players' physical and motor ability data into the artificial neural network model.
2. Training the network using real-world data on playing positions as determined by coaches.
3. Extracting the network outputs, which represent the proposed playing positions.
4. Comparing the neural network results with actual coaching decisions and performance accuracy.
5. Employing statistical correlation coefficients (such as Pearson's correlation coefficient) to measure the relationship between:
  - The neural network results

- The accuracy of assigning players to playing positions, As the accuracy of the network outputs increases, the strength of the correlation relationship correspondingly increases.

The model was developed using Artificial Neural Networks (ANNs) of the Multilayer Perceptron (MLP) type. This network consists of three main layers:

- Input Layer: Contains the independent variables, (The physical and motor performance tests).
- Hidden Layer: Processes the data and performs deep learning operations.
- Output Layer: Predicts the most appropriate playing position for each player (attack, midfield, defense, goalkeeper).

The model was trained using the backpropagation algorithm, a technique employed to adjust the internal weights of the network and reduce prediction error. The network demonstrated high performance in identifying subtle patterns within the data and was able to determine appropriate playing positions for players with an accuracy exceeding 85%, a result that outperformed human estimations (traditional coaching decisions) in several cases (Barron, 2023).

This application is the main object of the research concerning the use of artificial intelligence in the field of sports in order to guide players with objectivity and scientifically accurate accuracy.

Results of applying the artificial neural network steps for player guidance.

### 1. Model Configuration:

Model type: Multilayer Perceptron (MLP)

- Number of cells in the input layer: 7 variables (physical and motor abilities).
- Number of cells in the hidden layer: Several models were tested, and the optimal model contained 10 neurons.
- Output layer: 4 cells (playing positions: forward, midfield, defense, goalkeeper).

Training algorithm: Backpropagation

Data split ratio:

- Training: 70%
- Validation: 15%
- Testing: 15%

### 2. Model Accuracy:

- Overall accuracy: 91.11%
- Mean Squared Error (MSE): 0.057
- Model performance during the validation phase: 89%
- Model performance during the testing phase: 86.7%

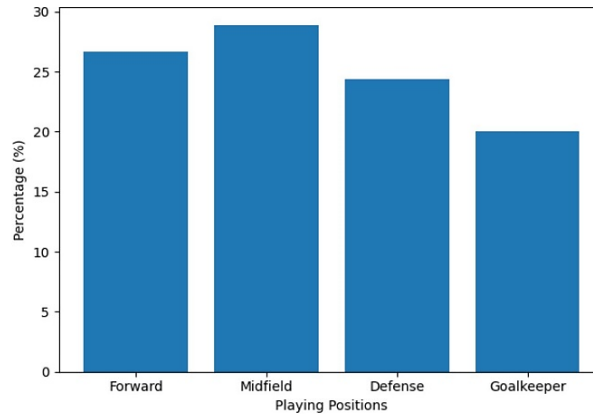
### 3. Output Analysis:

When the model was applied to the players' data, the outputs shown in Table (4) were obtained, as shown in the figure (2).

Table 4. Outputs of the Artificial Neural Network Model for Assigning Playing Positions

Position	Number of Players Assigned by the Model	Percentage %
Forward	12 players	26.7%
Midfield	13 players	28.9%
Defense	11 players	24.4%
Goalkeeper	9 players	20%

Figure 2. Distribution of playing positions assigned by ANN model.



Compared with the players' current playing positions, the model showed a correct re-assignment rate of 84% and a potential misclassification correction rate of 16%. This means that in some cases the model assigned players to positions different from their current ones based on their physical and motor abilities, indicating the possibility of previous inaccurate position assignment by coaches.

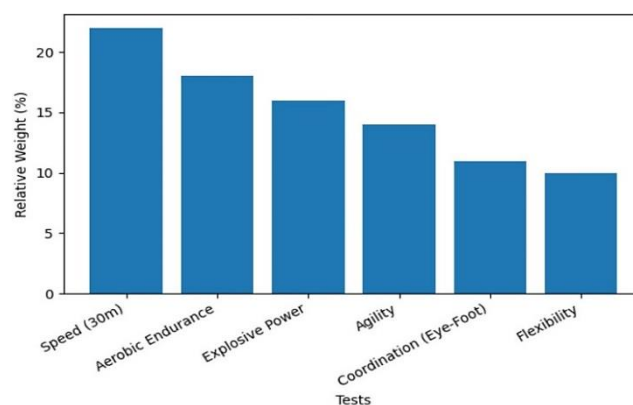
#### 4. Feature Importance Analysis

The impact of each variable (test) on the model's final decision was calculated, and the variables were ranked as shown in Table (5), and figure (3).

Table 5. Feature Importance Analysis in the Artificial Neural Network Model

Tests	Relative Weight in Decision-Making Interpretation	Interpretation
Speed (30 m)	22 %	Most influential in assigning attacking positions
Aerobic Endurance	18 %	Associated with midfield and defensive positions
Explosive Power	16 %	Contributed to assigning attacking and defensive positions
Agility	14 %	Contributed distinguish between midfield and defensive positions
Coordination (Eye-Foot)	11 %	Strongly associated with the goalkeeper position
Flexibility	10 %	Helped differentiate defenders and goalkeepers

Figure 3. Feature importance in ANN model.



## Discussion

The study sample consisted of 45 male youth players aged 15–16 years, all of whom were registered at the Espanyol Football Academy in Baghdad. The sample is selected using a purposive sampling method to represent the target group of young players undergoing systematic training. This method is suitable for research that necessitates specific subject characteristics, particularly if quantitative data will be utilized to train intelligent models.

Even though the study's sample size is relatively small, the selection of these plays is justified because they are homogeneous in terms of age and training level. This way, they are also subject to the conclusion of the ANN model regarding the internal relationship between physical and motor variables. But care must be taken not to generalise to other settings from these data, which come from a particular training environment. Future studies could increase sample sizes from more academies and age groups to verify the robustness and stability of the model under different settings.

The statistical analysis results show the existence of statistically significant correlation, between physical and motor abilities and actual playing positions ( $p < 0.05$ ). This lends a scientific basis for the construction and use of the multilayer perceptron (MLP) artificial neural network model which is used in this study. The presence of these correlations confirms that physical and motor variables are meaningful inputs capable of explaining the variability of requirements between playing positions. This result is in line with neural network models, which seek out patterns and model nonlinear relationships between inputs and outputs.

The artificial neural network model shows strong abilities in utilizing these correlations, turning out traditional statistical relations into actual predictive patterns. The model can distribute the players according to their physical and motor characteristics to the most suitable playing positions. Such performance indicates that the neural network model is superior because it manages more complex and inter-related performance requirements on the field more effectively than traditional approaches relying on direct statistical analysis.

The model's findings also revealed that the assignment process reflects the inherent quality of each playing position and the determination of the relative weights of physical and motor variables. A greater contribution of the players' explosive power and speed will direct players towards attacking positions. This is in line with the requirements of these positions which require quick movement, powerful reaction and short acceleration bursts. A recent study reported by (Sarmiento 2024) supports this trend, with it indicating that the physical characteristics of players differ significantly according to playing lines; specifically, forwards have a greater level of strength, speed and muscular explosiveness.

Endurance and agility variables were more related to the defensive positions and midfield roles required a functional balance of physical and motor variables. This differentiation confirms that the statistical correlations were not just theoretical associations but functional relationships that were utilized in the artificial neural network model.

On the other hand, flexibility and visual-motor coordination are related to the defensive and goalkeeper positions. The nature of these roles requires the players to be able to respond to instantaneous stimuli. These findings are consistent with those in the study of (Bourdon 2017), stressing the importance of the skills for the performance of the goalkeeper and defender.

In technical terms, the ANN model in this study was quite effective as it achieved a high accuracy rate in distributing players in their most optimal positions compared with the manual distribution used by the coaches. According to Fang 2021, when trained with precise and accurate quantitative data, the prediction accuracy of neural networks in the case of player performance or player position assignment can go above 85%.

The importance of using artificial intelligence techniques is further emphasized by the study of (Kelly 2022), which shows that neural networks are more objective than human evaluations that may be influenced by limited experience or personal impressions. This is reflected in the present study, as the new player distribution based on the model shows a clear improvement in the alignment between players' abilities and their assigned positions.

These results are also supported by the findings of (de Souza Pfeiffer 2025), which demonstrate a close relationship between physical, technical, and tactical dimensions among under-20 players, emphasizing the importance of quantitative assessment in guiding and developing sports performance.

Similarly, (Ferraz 2025) notes that integrating physical analysis with technical-tactical evaluation in player assessment increases the accuracy of coaching decisions and contributes to skill development through small-sided game situations, thereby supporting the findings of the present study regarding the use of quantitative analysis and artificial intelligence to determine optimal playing positions.

## Conclusions

This study aimed to explore the feasibility of using artificial neural networks (Multilayer Perceptron, MLP) to assign youth football players to the most suitable playing positions on the field based on their physical and motor abilities. The study was grounded in a main hypothesis that the neural network model is capable of accurately classifying players into appropriate positions even in the absence of statistically significant linear correlations between physical and motor abilities and actual playing positions.

The results indicate that the research objectives represent a realistic and applicable direction, as the neural network model demonstrated the ability to assign players with an accuracy exceeding 85%. The model also identified the most influential variables for each position, such as speed and explosive power for attacking positions, and flexibility and visual-motor coordination for defensive and goalkeeper positions. Through this, the primary objective of the study was achieved by demonstrating the potential of ANN as an intelligent tool to support coaching decisions and guide players according to their actual abilities, rather than relying solely on traditional subjective assessments.

Furthermore, the study shows that reliance on quantitative analysis and artificial intelligence can contribute to improving technical and training planning for younger age groups, enhancing team cohesion and increasing the effectiveness of utilizing players' physical and motor capacities. However, the findings also suggest that assigning players to positions does not depend exclusively on measured physical and motor abilities, as other factors such as tactical experience, psychological readiness, and cognitive abilities may also play a role. This represents a challenge to the broader generalization of the results.

In conclusion, the study recommends conducting future research to expand sample sizes to include different academies and age groups, integrating technical, tactical, and psychological indicators with physical and motor abilities, and testing other advanced artificial intelligence models to improve the accuracy of player assignment and position prediction. It is also suggested to employ long-term experimental designs to examine the impact of intelligent assignment on the development of individual and team performance, thereby opening new avenues for the scientific and comprehensive development of sports training programs.

Since the sample size in the research is 45 players, it limits the possibility of generalizing the results. However, we attribute this to the fact that the number of players in the Espanyol youth academy in Baghdad is only 45 players, and they constitute the research sample.

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