Construction of Value Classification Model by Tracking NBA Center Players' Performance with Virtual IoT Tagging Technology

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Abstract

Every basketball star's performance is an important asset and commodity for the coaches for personnel dispatch and team management. In this study, each star was regarded as an IoT object. National Basketball Association (NBA) centers were taken as an example to develop a traceable virtual tag. With the 15 items of game data published after each NBA game, synchronous tracking was linked, and the technique for order preference by similarity to ideal solution (TOPSIS) method was used to develop a relative value classification model for players of the same type from an objective point of view. The main contributions of this work are as follows: (1) Tampermonkey script is used to develop virtual IOT tags to track players' real-time game results, and (2) the model provides players with instant knowledge of their rankings relative to other players and provides reference for team management and commodity endorsement pricing.

Keywords: Virtual IoT tag, Player index, Relative value classification model, TOPSIS

1 Introduction

Smart homes and smart cities in the future will connect machines through Internet of things (IoT) technology, apply it in various fields of electronics and communication, and provide various services through digital management [1]. Gupta et al. [2] proposed the interconnection of sensors, electronic devices, and mobile phones with the IoT. With wireless networks (local-, wide-, and metropolitan-area networks) as the transmission interface, data and information can be shared for patient monitoring in remote areas, telemedicine, mobile healthcare, medical facility management, etc. With the commercialization of 5G technology, its application for sports enthusiasts can obtain quantitative data from daily exercise, sleep, eating habits, etc. for personal intelligent health management. It can collect physiological data anytime and anywhere and create a map of personal health through algorithmic analysis and evaluation. From hardware and software integration to smart cloud services and big-data analysis, the introduction of artificial-intelligence algorithms to the IoT platform has become the current market trend, and it also brings convenience and commercial value. For example, Andersons and Ritter [3] used radio frequency identification (RFID) technology to develop a high-precision timer and sports event management system, which occupies the leading position with 90% share in Latvia's sports market.

Tampermonkey script components can be used when running the Chrome browser to compare commodity prices, correct web page errors, and combine data from different web pages, or developers can define a variety of composite functions to modify what are shown on the website or to obtain information on the website. With browser security, Eves and Nicolaou [4] used Tampermonkey to develop electronic logs for the effective recording of simple codes, which assisted more than 31,000 surgeons in recording the disclosure of surgical information. Kumar et al. [5] used JavaScript to write Tampermonkey scripts, which can manipulate the user's browser to retrieve confidential data.

This study has two contributions. (1) Tampermonkey was used to develop virtual tag scripts for tracking virtual objects in the network. In Tampermonkey, these scripts can not only be used, but also be written, managed, and synchronized. (2) In the United States National Basketball Association (NBA) 2018-2019 season, for example, all players in the center position were regarded as virtual objects, and the results of each game were transmitted back to the database with a designated address through the IoT. Then, a relative value model of players of the same type was developed with the technique for order preference by similarity to ideal solution (TOPSIS) method to conduct real-time and synchronous analysis of players' relative rankings.

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It provides a decision-making analysis model for the coaching team and team management.

2 Literature Review

Many scholars [6-8] have proposed data envelopment analysis (DEA) to assess the efficiency indices and ranking of players. Mora et al. [9] used IoT technology to monitor players' heart rates during football matches. Through real-time data monitoring, sudden death and sports injury can be predicted. Kos and Umek [10] developed the SmartSki System, with which alpine skiing experts tested the skiing equipment sensors and body-attached sensor devices for one year. Through the IoT, the collected data of skiing parameters can be used to provide real-time feedback information for coaches and skiers and to adjust training methods with proper algorithms. Through analysis of wearable sensors and video recording, Michahelles and Schiele [11] improved the relationship between professional skiers and coaches and helped coaches identify the strengths and weaknesses of each skier. Halson [12] pointed out that an increasing number of athletes and coaches are collecting data on the perception of effort, heart rate, blood lactate, and training impulse through the IoT to propose training plans, analyze whether training is overloaded, and avoid sports injuries.

Yang [13] used the analytic hierarchy process and balanced scorecard to conduct constructive evaluation of retail stores using electronic shelf labels instead of paper labels as retail IoT infrastructure, providing important reference for retail stores, manufacturers, and service providers. Tiago and Paula [14] and Luo and Yang [15] developed smart tags for industrial IoT. Through wireless communication technology, they detect specific events triggered by the surrounding environment and provide feedback countermeasures at the same time. They are suitable for industrial 4.0 remote identification systems. In combination with the concepts of differential privacy requirements and k-anonymity, Wang et al. [16] proposed location-based services and developed the ε-DP ķ algorithm to query differentially private k-anonymity. Huang [17] combined the code generator, Java content repository, and virtual machines to create an adaptation process for IoT devices. According to the results, devices and sensors on the market can be connected to the IoT middleware faster and more efficiently, which reduces the process complexity and eliminates unnecessary human resources, hardware burden, and time consumption. Kopetz [18] pointed out that more intelligence is expected to be added to ID tags in the future, and the tagged objects will become intelligent objects, which can collect data through various transmission interfaces. The innovation of the IoT lies not in any new disruptive technology, but in the universal deployment of intelligent objects.

3 Evaluation Model

Hwang and Yoon [19] developed the TOPSIS method to solve multiple-attribute group decision making. The ideal solution based on an aggregating function representing closeness to the ideal, which originated in decision problem, maximizes the benefit criteria and minimizes the cost criteria. According to the concept of TOPSIS, the distance between the positive ideal solution and the negative ideal solution is defined to determine the ordering of all evaluation alternatives. The calculation steps are as follows [19-23].

Step 1: Establishing an evaluation decision matrix *D*.

The evaluation decision matrix ***D*** is represented as follows

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{pmatrix} X_1 & X_2 & \cdots & X_j & \cdots & X_n \end{pmatrix} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \vdots & x_{ij} & \vdots & x_{in} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad \textbf{(1)}$$

where A_i denotes the evaluated player i, i = 1, 2, ..., m; X_j represents the criterion of the evaluated player j, j=1, 2, ..., n; and data produced by players can be quantitative or qualitative. x_{ij} indicates the performance rating of the evaluated player A_i with respect to criterion X_j.

Step 2: Data normalization.

Data normalization can be calculated as

$$\text{for benefit criteria } r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \textbf{(2)}$$

$$\text{for cost criteria } r_{ij} = \frac{1/x_{ij}}{\sqrt{\sum_{i=1}^{m} 1/x_{ij}^2}} \quad \textbf{(3)}$$

for i = 1, 2, ..., m; j=1, 2, ..., n

Step 3: Establishing a weighted normalization matrix.

TOPSIS defines the weighted normalized performance matrix as

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1j} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2j} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ v_{i1} & v_{i2} & \vdots & v_{ij} & \vdots & v_{in} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mj} & \cdots & v_{mn} \end{bmatrix} \quad \textbf{(4)}$$

$v_{ij} = w_j \times r_{ij}$, for I = 1, 2, ..., m; j=1, 2, ..., n.

where w_j denotes the weight of criterion j.

Step 4: Calculating the separation measures.

The ideal solution is calculated based on the following equations:

$$d^+ = (v_1^+, v_2^+, \cdots, v_n^+), \text{ where } v_j^+ = \max_i v_{ij} \quad \textbf{(5)}$$

$$d^- = (v_1^-, v_2^-, \cdots, v_n^-), \text{ where } v_j^- = \min_i v_{ij} \quad \textbf{(6)}$$

The distance between the ideal solution and the negative ideal solution for each alternative is then calculated as

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \qquad i = 1, 2, \ldots, m, \quad \textbf{(7)}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \qquad i = 1, 2, \ldots, m, \quad \textbf{(8)}$$

Step 5: Calculating the relative closeness coefficient to the ideal solution, and ranking the center preference order.

The relative closeness to the ideal solution of each center preference is then calculated as

$$A_i^* = \frac{d_i^-}{d_i^+ + d_i^-}, \text{ for } i = 1, 2, \ldots, m \quad \textbf{(9)}$$

4 Value Analysis of NBA Centers

In the early days, basketball was dominated by centers, who were characterized by such prerequisites as a tall figure, explosive force, and crashworthiness. The trapezoidal block under the basket is the main scope of activities for centers. In this space, the center must perform important tasks, such as singles in the restricted area, pivot passing, rebound consolidation, and defensive blocking. If the center's explosive power or antagonism is insufficient, it is not easy to keep the restricted area, and the team has more difficulty winning. With the evolution of time and strategy, the skills needed for the center position have been transformed into stronger ball-holding capability, jump-shooting capability in wider areas, and mobility. However, the only unchanged requirement is the tall figure.

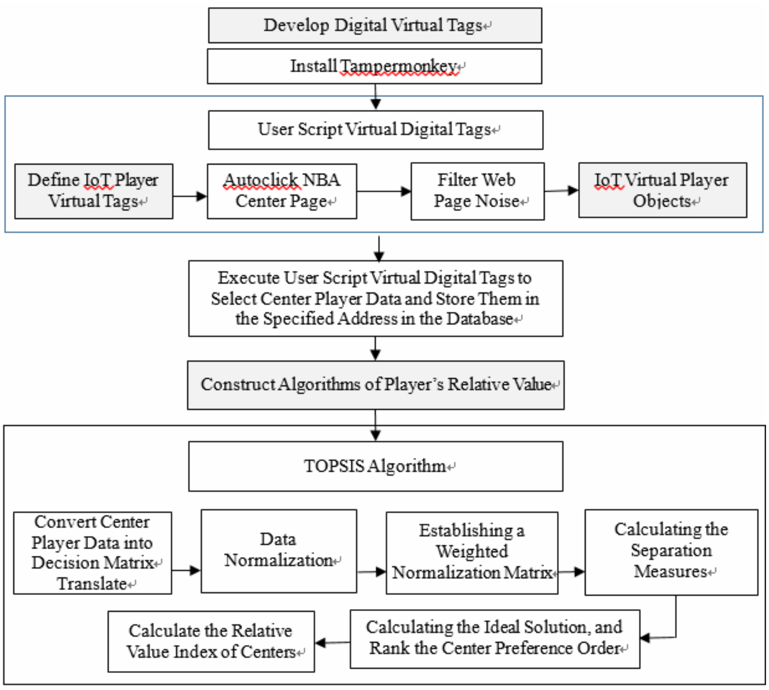

Figure 1. Research algorithms

To evaluate effectively the value of centers, this study constructed a value analysis model of athletes based on objective baseline data. First, a virtual tag script was constructed with Tampermonkey to click automatically on all the centers on the official NBA website, to track the results of each game automatically, and then to send the data back to the database with a designated address for storage. Then, using the TOPSIS analysis method, the relative value model of players was developed with 15 items of data published by the NBA: starter, rebounds (REB), assists (AST), minutes (MIN), efficiency (EFF), field goal percentage (FG%), three-pointer percentage (3P%), free-throw percentage (FT%), offensive rebound (OREB), defensive rebound (DREB), steals (STL), blocks (BLK), turnovers (TOV), fouls, and points (PTS) [24-25]. The relative ranking of centers is measured immediately according to the amount of information available. The algorithm is shown in Figure 1. Because each item of information had its own characteristics of uncertainty, the TOPSIS comprehensive evaluation value of each player was calculated completely from the angle of data being objective. Then, the TOPSIS comprehensive evaluation value calculated for each player was used to develop the value model of athletes of the same type. The calculation steps are as follows.

Step 1: Construct virtual tags and autoclick scripts with Tampermonkey.

First, after loading of the center page on the official NBA website, the JavaScript is run to track the data of each center automatically, to change the Chrome browser rendered HTML. The monitored data are then transferred to the database of the designated address for storage.

Step 2: Convert the data of 30 centers into the decision matrix.

Matches of the NBA 2018-2019 regular season were screened from the official NBA website. Each team had 82 matches in total. Provided that the average score of centers was more than 11.8, 30 qualified center players were eligible, as shown in Table 1.

Table 1. The original data of 30 centers in the NBA 2018-19 season

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Joel-Embiid	64	13.6	3.7	33.7	32.2	48.4	30	80.4	2.5	11.1	0.7	1.9	3.5	3.3	27.5
Anthony-Davis	56	12	3.9	33	33.4	51.7	33.1	79.4	3.1	8.9	1.6	2.4	2	2.4	25.9
Karl Anthony-Towns	77	12.4	3.4	33.1	30.4	51.8	40	83.6	3.4	9	0.9	1.6	3.1	3.8	24.4
Julius-Randle	49	8.7	3.1	30.6	22.8	52.4	34.4	73.1	2.2	6.5	0.7	0.6	2.8	3.4	21.4
LaMarcus-Aldridge	81	9.2	2.4	33.2	24.4	51.9	23.8	84.7	3.1	6.1	0.5	1.3	1.8	2.2	21.3
Nikola-Vucevic	80	12	3.8	31.4	28	51.8	36.4	78.9	2.8	9.2	1	1.1	2	2	20.8
Nikola-Jokic	80	10.8	7.3	31.3	28.9	51.1	30.7	82.1	2.9	8	1.4	0.7	3.1	2.9	20.1
John-Collins	59	9.8	2	30	23.2	56	34.8	76.3	3.6	6.2	0.4	0.6	2	3.3	19.5
Andre-Drummond	79	15.6	1.4	33.5	27.3	53.3	13.2	59	5.4	10.2	1.7	1.7	2.2	3.4	17.3
Kevin-Love	21	10.9	2.2	27.2	20.2	38.5	36.1	90.4	1.5	9.4	0.3	0.2	1.9	2.5	17
Clint-Capela	67	12.7	1.4	33.6	26.2	64.8	0	63.6	4.4	8.2	0.7	1.5	1.4	2.5	16.6
Montrezl-Harrell	5	6.5	2	26.3	19.7	61.5	17.6	64.3	2.2	4.3	0.9	1.3	1.6	3.1	16.6
Deandre-Ayton	70	10.3	1.8	30.7	22.6	58.5	0	74.6	3.1	7.1	0.9	0.9	1.8	2.9	16.3
DeMarcus-Cousins	30	8.2	3.6	25.7	20.8	48	27.4	73.6	1.4	6.8	1.3	1.5	2.4	3.6	16.3
Rudy-Gobert	80	12.9	2	31.8	27	66.9	0	63.6	3.8	9	0.8	2.3	1.6	2.9	15.9
Jusuf-Nurkic	72	10.4	3.2	27.4	22.5	50.8	10.3	77.3	3.4	7	1	1.4	2.3	3.5	15.6
Jonas-Valanciunas	27	8.6	1.4	22.3	19.6	55.9	29.2	79.5	2.2	6.4	0.4	1.1	1.8	3	15.6
Serge-Ibaka	51	8.1	1.3	27.2	18.6	52.9	29	76.3	2.1	6	0.4	1.4	1.5	2.9	15
Steven-Adams	80	9.5	1.6	33.4	19.7	59.5	0	50	4.9	4.6	1.5	1	1.7	2.6	13.9
Jaren-Jackson Jr.	56	4.7	1.1	26.1	14.4	50.6	35.9	76.6	1.3	3.4	0.9	1.4	1.7	3.8	13.8
Enes-Kanter	31	9.8	1.7	24.5	19.1	54.9	29.4	78.7	3.8	6	0.5	0.4	1.8	2.5	13.7
Marc-Gasol	72	7.9	4.4	30.8	19.3	44.8	36.3	75.9	1	6.9	1.1	1.1	2	2.7	13.6
Al-Horford	68	6.7	4.2	29	19.9	53.5	36	82.1	1.8	5	0.9	1.3	1.5	1.9	13.6
Myles-Turner	74	7.2	1.6	28.6	18.1	48.7	38.8	73.6	1.4	5.8	0.8	2.7	1.4	2.6	13.3
Dwight-Howard	9	9.2	0.4	25.6	16.9	62.3	0	60.4	2.7	6.6	0.8	0.4	1.8	3.8	12.8
Brook-Lopez	81	4.9	1.2	28.7	14.8	45.2	36.5	84.2	0.4	4.5	0.6	2.2	1	2.3	12.5
Hassan-Whiteside	53	11.3	0.8	23.3	19.7	57.1	12.5	44.9	3.6	7.8	0.6	1.9	1.3	2.7	12.3
JaVale-McGee	62	7.5	0.7	22.3	17.4	62.4	8.3	63.2	2.6	4.9	0.6	2	1.4	2.8	12
Willie-Cauley Stein	81	8.4	2.4	27.3	18	55.6	50	55.1	2.2	6.1	1.2	0.6	1	2.8	11.9
Derrick-Favors	70	7.4	1.2	23.2	17	58.6	21.8	67.5	2.7	4.6	0.7	1.4	1.1	2.1	11.8

Source: NBA, 2019 [24].

Step 3: Data normalization.

The principle is that, the larger the relevant beneficial indices, the better the results will be, including 13 indices of starter, REB, AST, MIN, EFF, FG%, 3P%, FT%, OREB, DREB, STL, BLK, and PTS. For relevant indices detrimental to players or teams, such as fouls leading to early send-off or team losing, then the smaller the indices, the better the results, including two indices of turnover and fouls that were normalized using Equations (2) and (3). The calculation results are shown in Table 2.

Table 2. Normalization of center data

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Joel-Embiid	0.1841	0.2509	0.2437	0.2118	0.2599	0.1627	0.1938	0.2005	0.1553	0.2853	0.1371	0.2363	0.0000	0.0855	0.2931
Anthony-Davis	0.1611	0.2214	0.2568	0.2074	0.2696	0.1738	0.2138	0.1980	0.1926	0.2288	0.3133	0.2985	0.1588	0.2394	0.2761
Karl Anthony-Towns	0.2215	0.2288	0.2239	0.2080	0.2454	0.1741	0.2584	0.2084	0.2112	0.2313	0.1762	0.1990	0.0424	0.0000	0.2601
Julius-Randle	0.1410	0.1605	0.2042	0.1923	0.1840	0.1761	0.2222	0.1823	0.1367	0.1671	0.1371	0.0746	0.0741	0.0684	0.2281
LaMarcus-Aldridge	0.2330	0.1697	0.1581	0.2087	0.1969	0.1744	0.1537	0.2112	0.1926	0.1568	0.0979	0.1617	0.1800	0.2736	0.2271
Nikola-Vucevic	0.2301	0.2214	0.2503	0.1973	0.2260	0.1741	0.2351	0.1967	0.1739	0.2365	0.1958	0.1368	0.1588	0.3078	0.2217
Nikola-Jokic	0.2301	0.1992	0.4808	0.1967	0.2333	0.1717	0.1983	0.2047	0.1801	0.2056	0.2741	0.0871	0.0424	0.1539	0.2143
John-Collins	0.1697	0.1808	0.1317	0.1885	0.1873	0.1882	0.2248	0.1902	0.2236	0.1594	0.0783	0.0746	0.1588	0.0855	0.2079
Andre-Drummond	0.2272	0.2878	0.0922	0.2105	0.2203	0.1791	0.0853	0.1471	0.3354	0.2622	0.3329	0.2115	0.1377	0.0684	0.1844
Kevin-Love	0.0604	0.2011	0.1449	0.1709	0.1630	0.1294	0.2332	0.2254	0.0932	0.2416	0.0587	0.0249	0.1694	0.2223	0.1812
Clint-Capela	0.1927	0.2343	0.0922	0.2112	0.2115	0.2178	0.0000	0.1586	0.2733	0.2108	0.1371	0.1866	0.2224	0.2223	0.1769
Montrezl-Harrell	0.0144	0.1199	0.1317	0.1653	0.1590	0.2067	0.1137	0.1603	0.1367	0.1105	0.1762	0.1617	0.2012	0.1197	0.1769
Deandre-Ayton	0.2014	0.1900	0.1185	0.1929	0.1824	0.1966	0.0000	0.1860	0.1926	0.1825	0.1762	0.1120	0.1800	0.1539	0.1738
DeMarcus-Cousins	0.0863	0.1513	0.2371	0.1615	0.1679	0.1613	0.1770	0.1835	0.0870	0.1748	0.2546	0.1866	0.1165	0.0342	0.1738
Rudy-Gobert	0.2301	0.2380	0.1317	0.1999	0.2179	0.2248	0.0000	0.1586	0.2361	0.2313	0.1567	0.2861	0.2012	0.1539	0.1695

Table 2. (continue)

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Jusuf-Nurkic	0.2071	0.1919	0.2107	0.1722	0.1816	0.1707	0.0665	0.1927	0.2112	0.1799	0.1958	0.1741	0.1271	0.0513	0.1663
Jonas-Valanciunas	0.0777	0.1587	0.0922	0.1402	0.1582	0.1879	0.1886	0.1982	0.1367	0.1645	0.0783	0.1368	0.1800	0.1368	0.1663
Serge-Ibaka	0.1467	0.1494	0.0856	0.1709	0.1501	0.1778	0.1873	0.1902	0.1304	0.1542	0.0783	0.1741	0.2118	0.1539	0.1599
Steven-Adams	0.2301	0.1753	0.1054	0.2099	0.1590	0.2000	0.0000	0.1247	0.3044	0.1182	0.2937	0.1244	0.1906	0.2052	0.1482
Jaren-Jackson Jr.	0.1611	0.0867	0.0724	0.1640	0.1162	0.1701	0.2319	0.1910	0.0808	0.0874	0.1762	0.1741	0.1906	0.0000	0.1471
Enes-Kanter	0.0892	0.1808	0.1120	0.1540	0.1542	0.1845	0.1899	0.1962	0.2361	0.1542	0.0979	0.0498	0.1800	0.2223	0.1460
Marc-Gasol	0.2071	0.1457	0.2898	0.1936	0.1558	0.1506	0.2345	0.1892	0.0621	0.1773	0.2154	0.1368	0.1588	0.1881	0.1450
Al-Horford	0.1956	0.1236	0.2766	0.1823	0.1606	0.1798	0.2325	0.2047	0.1118	0.1285	0.1762	0.1617	0.2118	0.3249	0.1450
Myles-Turner	0.2129	0.1328	0.1054	0.1797	0.1461	0.1637	0.2506	0.1835	0.0870	0.1491	0.1567	0.3359	0.2224	0.2052	0.1418
Dwight-Howard	0.0259	0.1697	0.0263	0.1609	0.1364	0.2094	0.0000	0.1506	0.1677	0.1696	0.1567	0.0498	0.1800	0.0000	0.1364
Brook-Lopez	0.2330	0.0904	0.0790	0.1804	0.1195	0.1519	0.2358	0.2099	0.0248	0.1157	0.1175	0.2737	0.2647	0.2565	0.1332
Hassan-Whiteside	0.1525	0.2085	0.0527	0.1464	0.1590	0.1919	0.0807	0.1119	0.2236	0.2005	0.1175	0.2363	0.2330	0.1881	0.1311
JaVale-McGee	0.1783	0.1384	0.0461	0.1402	0.1404	0.2097	0.0536	0.1576	0.1615	0.1259	0.1175	0.2488	0.2224	0.1710	0.1279
Willie-Cauley Stein	0.2330	0.1550	0.1581	0.1716	0.1453	0.1869	0.3230	0.1374	0.1367	0.1568	0.2350	0.0746	0.2647	0.1710	0.1268
Derrick-Favors	0.2014	0.1365	0.0790	0.1458	0.1372	0.1969	0.1408	0.1683	0.1677	0.1182	0.1371	0.1741	0.2541	0.2907	0.1258

Step 4: Establishing a weighted normalization matrix.

Equation (4) was used to calculate the weighted normalized decision matrix. In this research, the decision maker assumes that all evaluation criteria are weighted the same, and the results are shown in Table 3.

Table 3. Weighted normalization center matrix

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Joel-Embiid	0.0123	0.0167	0.0162	0.0141	0.0173	0.0108	0.0129	0.0134	0.0104	0.0190	0.0091	0.0158	0.0000	0.0057	0.0195
Anthony-Davis	0.0107	0.0148	0.0171	0.0138	0.0180	0.0116	0.0143	0.0132	0.0128	0.0153	0.0209	0.0199	0.0106	0.0160	0.0184
Karl Anthony-Towns	0.0148	0.0153	0.0149	0.0139	0.0164	0.0116	0.0172	0.0139	0.0141	0.0154	0.0117	0.0133	0.0028	0.0000	0.0173
Julius-Randle	0.0094	0.0107	0.0136	0.0128	0.0123	0.0117	0.0148	0.0122	0.0091	0.0111	0.0091	0.0050	0.0049	0.0046	0.0152
LaMarcus-Aldridge	0.0155	0.0113	0.0105	0.0139	0.0131	0.0116	0.0102	0.0141	0.0128	0.0105	0.0065	0.0108	0.0120	0.0182	0.0151
Nikola-Vucevic	0.0153	0.0148	0.0167	0.0132	0.0151	0.0116	0.0157	0.0131	0.0116	0.0158	0.0131	0.0091	0.0106	0.0205	0.0148
Nikola-Jokic	0.0153	0.0133	0.0321	0.0131	0.0156	0.0114	0.0132	0.0136	0.0120	0.0137	0.0183	0.0058	0.0028	0.0103	0.0143
John-Collins	0.0113	0.0121	0.0088	0.0126	0.0125	0.0125	0.0150	0.0127	0.0149	0.0106	0.0052	0.0050	0.0106	0.0057	0.0139
Andre-Drummond	0.0151	0.0192	0.0061	0.0140	0.0147	0.0119	0.0057	0.0098	0.0224	0.0175	0.0222	0.0141	0.0092	0.0046	0.0123
Kevin-Love	0.0040	0.0134	0.0097	0.0114	0.0109	0.0086	0.0155	0.0150	0.0062	0.0161	0.0039	0.0017	0.0113	0.0148	0.0121
Clint-Capela	0.0128	0.0156	0.0061	0.0141	0.0141	0.0145	0.0000	0.0106	0.0182	0.0141	0.0091	0.0124	0.0148	0.0148	0.0118
Montrezl-Harrell	0.0010	0.0080	0.0088	0.0110	0.0106	0.0138	0.0076	0.0107	0.0091	0.0074	0.0117	0.0108	0.0134	0.0080	0.0118
Deandre-Ayton	0.0134	0.0127	0.0079	0.0129	0.0122	0.0131	0.0000	0.0124	0.0128	0.0122	0.0117	0.0075	0.0120	0.0103	0.0116
DeMarcus-Cousins	0.0058	0.0101	0.0158	0.0108	0.0112	0.0108	0.0118	0.0122	0.0058	0.0117	0.0170	0.0124	0.0078	0.0023	0.0116
Rudy-Gobert	0.0153	0.0159	0.0088	0.0133	0.0145	0.0150	0.0000	0.0106	0.0157	0.0154	0.0104	0.0191	0.0134	0.0103	0.0113
Jusuf-Nurkic	0.0138	0.0128	0.0140	0.0115	0.0121	0.0114	0.0044	0.0128	0.0141	0.0120	0.0131	0.0116	0.0085	0.0034	0.0111
Jonas-Valanciunas	0.0052	0.0106	0.0061	0.0093	0.0105	0.0125	0.0126	0.0132	0.0091	0.0110	0.0052	0.0091	0.0120	0.0091	0.0111
Serge-Ibaka	0.0098	0.0100	0.0057	0.0114	0.0100	0.0119	0.0125	0.0127	0.0087	0.0103	0.0052	0.0116	0.0141	0.0103	0.0107
Steven-Adams	0.0153	0.0117	0.0070	0.0140	0.0106	0.0133	0.0000	0.0083	0.0203	0.0079	0.0196	0.0083	0.0127	0.0137	0.0099
Jaren-Jackson Jr.	0.0107	0.0058	0.0048	0.0109	0.0077	0.0113	0.0155	0.0127	0.0054	0.0058	0.0117	0.0116	0.0127	0.0000	0.0098
Enes-Kanter	0.0059	0.0121	0.0075	0.0103	0.0103	0.0123	0.0127	0.0131	0.0157	0.0103	0.0065	0.0033	0.0120	0.0148	0.0097
Marc-Gasol	0.0138	0.0097	0.0193	0.0129	0.0104	0.0100	0.0156	0.0126	0.0041	0.0118	0.0144	0.0091	0.0106	0.0125	0.0097
Al-Horford	0.0130	0.0082	0.0184	0.0122	0.0107	0.0120	0.0155	0.0136	0.0075	0.0086	0.0117	0.0108	0.0141	0.0217	0.0097
Myles-Turner	0.0142	0.0089	0.0070	0.0120	0.0097	0.0109	0.0167	0.0122	0.0058	0.0099	0.0104	0.0224	0.0148	0.0137	0.0095
Dwight-Howard	0.0017	0.0113	0.0018	0.0107	0.0091	0.0140	0.0000	0.0100	0.0112	0.0113	0.0104	0.0033	0.0120	0.0000	0.0091
Brook-Lopez	0.0155	0.0060	0.0053	0.0120	0.0080	0.0101	0.0157	0.0140	0.0017	0.0077	0.0078	0.0182	0.0176	0.0171	0.0089
Hassan-Whiteside	0.0102	0.0139	0.0035	0.0098	0.0106	0.0128	0.0054	0.0075	0.0149	0.0134	0.0078	0.0158	0.0155	0.0125	0.0087
JaVale-McGee	0.0119	0.0092	0.0031	0.0093	0.0094	0.0140	0.0036	0.0105	0.0108	0.0084	0.0078	0.0166	0.0148	0.0114	0.0085
Willie-Cauley Stein	0.0155	0.0103	0.0105	0.0114	0.0097	0.0125	0.0215	0.0092	0.0091	0.0105	0.0157	0.0050	0.0176	0.0114	0.0085
Derrick-Favors	0.0134	0.0091	0.0053	0.0097	0.0091	0.0131	0.0094	0.0112	0.0112	0.0079	0.0091	0.0116	0.0169	0.0194	0.0084

Step 5: Calculating the separation measures.

Equations (7) and (8) were used to calculate the separation measure of the ideal grade (benefit criteria) and negative grade (cost criteria) of 30 centers, as shown in Table 4 and Table 5.

Table 4. The distance between the ideal solution

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Joel-Embiid	0.0033	0.0025	0.0158	0.0000	0.0006	0.0041	0.0086	0.0017	0.0120	0.0000	0.0131	0.0066	0.0176	0.0160	0.0000
Anthony-Davis	0.0048	0.0044	0.0149	0.0003	0.0000	0.0034	0.0073	0.0018	0.0095	0.0038	0.0013	0.0025	0.0071	0.0057	0.0011
Karl Anthony-Towns	0.0008	0.0039	0.0171	0.0003	0.0016	0.0034	0.0043	0.0011	0.0083	0.0036	0.0104	0.0091	0.0148	0.0217	0.0022
Julius-Randle	0.0061	0.0085	0.0184	0.0013	0.0057	0.0032	0.0067	0.0029	0.0133	0.0079	0.0131	0.0174	0.0127	0.0171	0.0043
LaMarcus-Aldridge	0.0000	0.0079	0.0215	0.0002	0.0048	0.0034	0.0113	0.0009	0.0095	0.0086	0.0157	0.0116	0.0056	0.0034	0.0044
Nikola-Vucevic	0.0002	0.0044	0.0154	0.0010	0.0029	0.0034	0.0059	0.0019	0.0108	0.0033	0.0091	0.0133	0.0071	0.0011	0.0048
Nikola-Jokic	0.0002	0.0059	0.0000	0.0010	0.0024	0.0035	0.0083	0.0014	0.0104	0.0053	0.0039	0.0166	0.0148	0.0114	0.0053
John-Collins	0.0042	0.0071	0.0233	0.0016	0.0055	0.0024	0.0065	0.0023	0.0075	0.0084	0.0170	0.0174	0.0071	0.0160	0.0057
Andre-Drummond	0.0004	0.0000	0.0259	0.0001	0.0033	0.0030	0.0158	0.0052	0.0000	0.0015	0.0000	0.0083	0.0085	0.0171	0.0072
Kevin-Love	0.0115	0.0058	0.0224	0.0027	0.0071	0.0064	0.0060	0.0000	0.0162	0.0029	0.0183	0.0207	0.0064	0.0068	0.0075
Clint-Capela	0.0027	0.0036	0.0259	0.0000	0.0039	0.0005	0.0215	0.0045	0.0041	0.0050	0.0131	0.0100	0.0028	0.0068	0.0077
Montrezl-Harrell	0.0146	0.0112	0.0233	0.0031	0.0074	0.0012	0.0140	0.0043	0.0133	0.0117	0.0104	0.0116	0.0042	0.0137	0.0077

Table 4. (continue)

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Deandre-Ayton	0.0021	0.0065	0.0241	0.0013	0.0058	0.0019	0.0215	0.0026	0.0095	0.0069	0.0104	0.0149	0.0056	0.0114	0.0080
DeMarcus-Cousins	0.0098	0.0091	0.0162	0.0034	0.0068	0.0042	0.0097	0.0028	0.0166	0.0074	0.0052	0.0100	0.0099	0.0194	0.0080
Rudy-Gobert	0.0002	0.0033	0.0233	0.0008	0.0034	0.0000	0.0215	0.0045	0.0066	0.0036	0.0117	0.0033	0.0042	0.0114	0.0082
Jusuf-Nurkic	0.0017	0.0064	0.0180	0.0026	0.0059	0.0036	0.0171	0.0022	0.0083	0.0070	0.0091	0.0108	0.0092	0.0182	0.0085
Jonas-Valanciunas	0.0104	0.0086	0.0259	0.0048	0.0074	0.0025	0.0090	0.0018	0.0133	0.0081	0.0170	0.0133	0.0056	0.0125	0.0085
Serge-Ibaka	0.0058	0.0092	0.0263	0.0027	0.0080	0.0031	0.0090	0.0023	0.0137	0.0087	0.0170	0.0108	0.0035	0.0114	0.0089
Steven-Adams	0.0002	0.0075	0.0250	0.0001	0.0074	0.0017	0.0215	0.0067	0.0021	0.0111	0.0026	0.0141	0.0049	0.0080	0.0097
Jaren-Jackson Jr.	0.0048	0.0134	0.0272	0.0032	0.0102	0.0037	0.0061	0.0023	0.0170	0.0132	0.0104	0.0108	0.0049	0.0217	0.0097
Enes-Kanter	0.0096	0.0071	0.0246	0.0039	0.0077	0.0027	0.0089	0.0019	0.0066	0.0087	0.0157	0.0191	0.0056	0.0068	0.0098
Marc-Gasol	0.0017	0.0095	0.0127	0.0012	0.0076	0.0050	0.0059	0.0024	0.0182	0.0072	0.0078	0.0133	0.0071	0.0091	0.0099
Al-Horford	0.0025	0.0109	0.0136	0.0020	0.0073	0.0030	0.0060	0.0014	0.0149	0.0105	0.0104	0.0116	0.0035	0.0000	0.0099
Myles-Turner	0.0013	0.0103	0.0250	0.0021	0.0082	0.0041	0.0048	0.0028	0.0166	0.0091	0.0117	0.0000	0.0028	0.0080	0.0101
Dwight-Howard	0.0138	0.0079	0.0303	0.0034	0.0089	0.0010	0.0215	0.0050	0.0112	0.0077	0.0117	0.0191	0.0056	0.0217	0.0104
Brook-Lopez	0.0000	0.0132	0.0268	0.0021	0.0100	0.0049	0.0058	0.0010	0.0207	0.0113	0.0144	0.0041	0.0000	0.0046	0.0107
Hassan-Whiteside	0.0054	0.0053	0.0285	0.0044	0.0074	0.0022	0.0161	0.0076	0.0075	0.0057	0.0144	0.0066	0.0021	0.0091	0.0108
JaVale-McGee	0.0036	0.0100	0.0290	0.0048	0.0086	0.0010	0.0180	0.0045	0.0116	0.0106	0.0144	0.0058	0.0028	0.0103	0.0110
Willie-Cauley Stein	0.0000	0.0089	0.0215	0.0027	0.0083	0.0025	0.0000	0.0059	0.0133	0.0086	0.0065	0.0174	0.0000	0.0103	0.0111
Derrick-Favors	0.0021	0.0101	0.0268	0.0044	0.0088	0.0019	0.0121	0.0038	0.0112	0.0111	0.0131	0.0108	0.0007	0.0023	0.0112

Table 5. The distance between the negative solution

Player Name	Starter	REB	AST	MIN	EFF	FG%	3P%	FT%	OREB	DREB	STL	BLK	TOV	Foul	PTS
Joel-Embiid	0.0113	0.0109	0.0145	0.0048	0.0096	0.0022	0.0129	0.0059	0.0087	0.0132	0.0052	0.0141	0.0000	0.0057	0.0112
Anthony-Davis	0.0098	0.0090	0.0154	0.0045	0.0102	0.0030	0.0143	0.0057	0.0112	0.0094	0.0170	0.0182	0.0106	0.0160	0.0100
Karl Anthony-Towns	0.0138	0.0095	0.0132	0.0045	0.0086	0.0030	0.0172	0.0064	0.0124	0.0096	0.0078	0.0116	0.0028	0.0000	0.0090
Julius-Randle	0.0084	0.0049	0.0119	0.0035	0.0045	0.0031	0.0148	0.0047	0.0075	0.0053	0.0052	0.0033	0.0049	0.0046	0.0068
LaMarcus-Aldridge	0.0146	0.0055	0.0088	0.0046	0.0054	0.0030	0.0102	0.0066	0.0112	0.0046	0.0026	0.0091	0.0120	0.0182	0.0068
Nikola-Vucevic	0.0144	0.0090	0.0149	0.0038	0.0073	0.0030	0.0157	0.0057	0.0099	0.0099	0.0091	0.0075	0.0106	0.0205	0.0064
Nikola-Jokic	0.0144	0.0075	0.0303	0.0038	0.0078	0.0028	0.0132	0.0062	0.0104	0.0079	0.0144	0.0041	0.0028	0.0103	0.0059
John-Collins	0.0104	0.0063	0.0070	0.0032	0.0047	0.0039	0.0150	0.0052	0.0133	0.0048	0.0013	0.0033	0.0106	0.0057	0.0055
Andre-Drummond	0.0142	0.0134	0.0044	0.0047	0.0069	0.0033	0.0057	0.0023	0.0207	0.0117	0.0183	0.0124	0.0092	0.0046	0.0039
Kevin-Love	0.0031	0.0076	0.0079	0.0021	0.0031	0.0000	0.0155	0.0076	0.0046	0.0103	0.0000	0.0000	0.0113	0.0148	0.0037
Clint-Capela	0.0119	0.0098	0.0044	0.0047	0.0063	0.0059	0.0000	0.0031	0.0166	0.0082	0.0052	0.0108	0.0148	0.0148	0.0034
Montrezl-Harrell	0.0000	0.0022	0.0070	0.0017	0.0029	0.0052	0.0076	0.0032	0.0075	0.0015	0.0078	0.0091	0.0134	0.0080	0.0034
Deandre-Ayton	0.0125	0.0069	0.0061	0.0035	0.0044	0.0045	0.0000	0.0049	0.0112	0.0063	0.0078	0.0058	0.0120	0.0103	0.0032
DeMarcus-Cousins	0.0048	0.0043	0.0140	0.0014	0.0034	0.0021	0.0118	0.0048	0.0041	0.0058	0.0131	0.0108	0.0078	0.0023	0.0032
Rudy-Gobert	0.0144	0.0101	0.0070	0.0040	0.0068	0.0064	0.0000	0.0031	0.0141	0.0096	0.0065	0.0174	0.0134	0.0103	0.0029
Jusuf-Nurkic	0.0128	0.0070	0.0123	0.0021	0.0044	0.0028	0.0044	0.0054	0.0124	0.0062	0.0091	0.0100	0.0085	0.0034	0.0027
Jonas-Valanciunas	0.0042	0.0048	0.0044	0.0000	0.0028	0.0039	0.0126	0.0058	0.0075	0.0051	0.0013	0.0075	0.0120	0.0091	0.0027
Serge-Ibaka	0.0088	0.0042	0.0040	0.0021	0.0023	0.0032	0.0125	0.0052	0.0070	0.0045	0.0013	0.0100	0.0141	0.0103	0.0023
Steven-Adams	0.0144	0.0059	0.0053	0.0047	0.0029	0.0047	0.0000	0.0008	0.0186	0.0021	0.0157	0.0066	0.0127	0.0137	0.0015
Jaren-Jackson Jr.	0.0098	0.0000	0.0031	0.0016	0.0000	0.0027	0.0155	0.0053	0.0037	0.0000	0.0078	0.0100	0.0127	0.0000	0.0014
Enes-Kanter	0.0050	0.0063	0.0057	0.0009	0.0025	0.0037	0.0127	0.0056	0.0141	0.0045	0.0026	0.0017	0.0120	0.0148	0.0014
Marc-Gasol	0.0128	0.0039	0.0176	0.0036	0.0026	0.0014	0.0156	0.0052	0.0025	0.0060	0.0104	0.0075	0.0106	0.0125	0.0013
Al-Horford	0.0121	0.0025	0.0167	0.0028	0.0030	0.0034	0.0155	0.0062	0.0058	0.0027	0.0078	0.0091	0.0141	0.0217	0.0013
Myles-Turner	0.0132	0.0031	0.0053	0.0026	0.0020	0.0023	0.0167	0.0048	0.0041	0.0041	0.0065	0.0207	0.0148	0.0137	0.0011
Dwight-Howard	0.0008	0.0055	0.0000	0.0014	0.0013	0.0053	0.0000	0.0026	0.0095	0.0055	0.0065	0.0017	0.0120	0.0000	0.0007
Brook-Lopez	0.0146	0.0002	0.0035	0.0027	0.0002	0.0015	0.0157	0.0065	0.0000	0.0019	0.0039	0.0166	0.0176	0.0171	0.0005
Hassan-Whiteside	0.0092	0.0081	0.0018	0.0004	0.0029	0.0042	0.0054	0.0000	0.0133	0.0075	0.0039	0.0141	0.0155	0.0125	0.0004
JaVale-McGee	0.0109	0.0034	0.0013	0.0000	0.0016	0.0054	0.0036	0.0030	0.0091	0.0026	0.0039	0.0149	0.0148	0.0114	0.0001
Willie-Cauley Stein	0.0146	0.0046	0.0088	0.0021	0.0019	0.0038	0.0215	0.0017	0.0075	0.0046	0.0117	0.0033	0.0176	0.0114	0.0001
Derrick-Favors	0.0125	0.0033	0.0035	0.0004	0.0014	0.0045	0.0094	0.0038	0.0095	0.0021	0.0052	0.0100	0.0169	0.0194	0.0000

Step 6: Calculating the ideal solution, and ranking the center preference order.

Equation (9) was used to calculate the relative closeness coefficient A_i^* of 30 centers, as shown in the right-most column of Table 6.

Table 6. Outcome of the TOPSIS, A_i^* of 30 centers

Player Name	d^+	d^-	TOPSIS A_i^*
Joel-Embiid	0.0359	0.0376	0.5117
Anthony-Davis	0.0230	0.0456	0.6648
Karl Anthony-Towns	0.0362	0.0378	0.5105
Julius-Randle	0.0416	0.0271	0.3942
LaMarcus-Aldridge	0.0360	0.0359	0.4992
Nikola-Vucevic	0.0278	0.0421	0.6023
Nikola-Jokic	0.0305	0.0449	0.5958
John-Collins	0.0418	0.0297	0.4151
Andre-Drummond	0.0382	0.0411	0.5187
Kevin-Love	0.0445	0.0305	0.4068

Table 6. (continue)

Player Name	d^+	d^-	TOPSIS A_i^*
Clint-Capela	0.0402	0.0361	0.4730
Montrezl-Harrell	0.0445	0.0248	0.3584
Deandre-Ayton	0.0428	0.0289	0.4031
DeMarcus-Cousins	0.0401	0.0289	0.4182
Rudy-Gobert	0.0383	0.0374	0.4939
Jusuf-Nurkic	0.0391	0.0302	0.4359
Jonas-Valanciunas	0.0446	0.0255	0.3636
Serge-Ibaka	0.0432	0.0282	0.3946
Steven-Adams	0.0420	0.0362	0.4632
Jaren-Jackson Jr.	0.0489	0.0268	0.3543
Enes-Kanter	0.0426	0.0300	0.4135
Marc-Gasol	0.0351	0.0355	0.5029
Al-Horford	0.0332	0.0399	0.5461
Myles-Turner	0.0390	0.0380	0.4934
Dwight-Howard	0.0552	0.0195	0.2612
Brook-Lopez	0.0444	0.0377	0.4595
Hassan-Whiteside	0.0425	0.0325	0.4328
JaVale-McGee	0.0460	0.0294	0.3899
Willie-Cauley Stein	0.0385	0.0383	0.4988
Derrick-Favors	0.0419	0.0345	0.4515

Step 7: Calculating the value index of 30 centers.

The 30 centers were ranked by TOPSIS, and the results are shown in Table 7. The results of A_i^* calculated from Table 7 divided the centers into four different value classes of ABCD to evaluate centers' relative value. There were eight A-Class centers with $A_i^* \geq 0.5$, eight B-Class centers with $0.45 \leq A_i^* < 0.5$, seven C-Class centers with $0.4 \leq A_i^* < 0.45$, and seven D-Class centers with $A_i^* < 0.4$.

Table 7. TOPSIS rankings and value indexes of 30 centers

Name	TOPSIS	Rank	Value
Anthony-Davis	0.6648	1	A
Nikola-Vucevic	0.6023	2	A
Nikola-Jokic	0.5958	3	A
Al-Horford	0.5461	4	A
Andre-Drummond	0.5187	5	A
Joel-Embiid	0.5117	6	A
Karl Anthony-Towns	0.5105	7	A
Marc-Gasol	0.5029	8	A
LaMarcus-Aldridge	0.4992	9	B
Willie-Cauley Stein	0.4988	10	B
Rudy-Gobert	0.4939	11	B
Myles-Turner	0.4934	12	B
Clint-Capela	0.4730	13	B
Steven-Adams	0.4632	14	B
Brook-Lopez	0.4595	15	B
Derrick-Favors	0.4515	16	B
Jusuf-Nurkic	0.4359	17	C
Hassan-Whiteside	0.4328	18	C
DeMarcus-Cousins	0.4182	19	C
John-Collins	0.4151	20	C
Enes-Kanter	0.4135	21	C
Kevin-Love	0.4068	22	C
Deandre-Ayton	0.4031	23	C
Serge-Ibaka	0.3946	24	D
Julius-Randle	0.3942	25	D
JaVale-McGee	0.3899	26	D
Jonas-Valanciunas	0.3636	27	D
Montrezl-Harrell	0.3584	28	D
Jaren-Jackson Jr.	0.3543	29	D
Dwight-Howard	0.2612	30	D

Ten centers were selected by sorting out the GRD Rank, NBA [18], Sports Vision Rank [19], Pure Magic Rank [20], and Bleacher Report [21]. Results are shown in Table 8. According to Table 8, the orders of the top 10 centers in these five types of ranking are slightly different. This study provides another method of calculation with dynamic and instant monitoring of centers' relative values.

Table 8. Ranking Best Centers in 2018-19

Rank	TOPSIS Rank	NBA's Rank	Sports Rank [25]	Pure Magic Rank [26]	Bleacher Report [27]
1	Anthony-Davis	Joel-Embiid	Joel-Embiid	Anthony Davis	Anthony Davis
2	Nikola-Vucevic	Anthony-Davis	Nikola-Jokic	Joel Embiid	Joel Embiid
3	Nikola-Jokic	Karl Anthony-Towns	Karl Anthony-Towns	Rudy Gobert	Rudy Gobert
4	Al-Horford	Julius-Randle	Nikola-Vucevic	Karl-Anthony Towns	Nikola Jokic
5	Andre-Drummond	LaMarcus-Aldridge	Rudy-Gobert	Deandre Ayton	Karl-Anthony Towns
6	Joel-Embiid	Nikola-Vucevic	Andre-Drummond	Clint Capela	Al Horford
7	Karl Anthony-Towns	Nikola-Jokic	Julius-Randle	Nikola Jokic	Andre Drummond
8	Marc-Gasol	John-Collins	Clint-Capela	Al Horford	Clint Capela
9	LaMarcus-Aldridge	Andre-Drummond	Steven-Adams	Nikola Vucevic	Steven Adams
10	Willie-Cauley Stein	Kevin-Love	Al-Horford	Andre Drummond	Myles Turner

5 Conclusion

Centers should have a certain degree of mobility. It is more important to determine the direction of rebounds and take-off time correctly. They are important defensive players in the restricted area. The quality of such skills as jump shots, inside shots, or dunking is very important. This study objectively calculates the data obtained from the match on the court. The results and conclusions are as follows.

(1) In this study, the use of the TOPSIS method to calculate the value analysis indices of players was proposed. Using the data of players in each match and analyzing the players' conditions with objective data, the purpose is not to predict and grasp everything that happens on the basketball court, but to maximize the occurrence probability of beneficial events or to minimize the chance of adverse events. The rest is determined by the players on the court.

(2) There are many unpredictable variables in the course of the game, and they are not in the scope of this study. Examples include the factors that affect the players' mentality and mood, such as coaches' communication and leadership skills, referees, fans on the sidelines, or home and away fields, which may affect the analysis accuracy.

(3) This study provided a value index model for evaluating NBA centers. If the basketball teams want to study the value indices of different positions, such as forward and guard, they can set different positions and calculate the value evaluation indices with the algorithms proposed in this study. Thus, the players' conditions can be inspected to maintain the performance of the team.

(4) Table 1 shows that Kevin Love, Montrezl Harrell, DeMarcus Cousins, Jonas Valanciunas, Enes Kanter, and Dwight Howard had fewer than 41 times as starters, which did not reach half of the games they attended. To be fair, these players should be excluded from the ranking.

(5) Sports Vision [19] rankings assume that they can be selected to play the rest of the season and consider the current health conditions of the players. However, distant injury history and long-term future planning are not considered. In addition, players who missed the whole season are not included in the selection. Adding these sequencing rules to the model can be considered.

(6) This study used NBA 2018-2019 season data for analysis, compared with the 10 centers selected by NBA, Sports Vision Rank, Pure Magic Rank, and Bleacher Report. For future research directions, it is planned to use multiple-season data to compare different research methods.

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Biography

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