APPLICATION OF THE AHP METHOD IN SELECTING BASEBALL PITCHERS

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ABSTRACT

The use of scientific methods to determine performance results and analyze the effectiveness of sports players constitutes a powerful tool that can help coaches and teams make better decisions and adequately use available resources. Pitcher selection is a strategic decision that significantly influences the performance of a professional baseball team. In this study, Analytic Hierarchy Process (AHP) models were built to rank the performance of baseball pitchers in Major League Baseball (MLB) in the United States. There are three relevant aspects of this research. First, the models allow the evaluation of the overall performance of the pitcher, considering his skills and performance as a pitcher as well as his fielding and batting contributions. To evaluate the overall performance of a pitcher, well-known standard professional baseball statistics were used. Second, to highlight the flexibility of the model, four models were created according to the type of pitcher (starter or reliever) and the league in which he plays (American or National league). Finally, a distinctive feature of the models is their general scope. The experts were only required to determine the best criteria and subcriteria and the priorities of the hierarchical structure of the models, but they were not needed to rank the pitchers (alternatives). The models were applied to different emblematic MLB awards and the results produced by the models coincide with the pitchers who actually won the awards.

Keywords: Analytic Hierarchy Process; AHP; baseball; pitchers; Major League Baseball; MLB

1. Introduction

In the United States, baseball is a multimillion-dollar industry. License and sponsorship agreements, game broadcasting contracts, and profits produced by attendance at stadiums generate large revenues (Powers, 2015; Lee, 2018). It is also a sport where a huge amount of statistical data is extracted and stored for each game. Data records by player, team, and position are recorded for each inning, game, series, and season. Because of this, viewers

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are constantly waiting for a record to be broken. The fans want to be witnesses in the stadium or through a televised game to a historical event.

Each year at the end of the MLB regular season, the most valuable player, the best pitcher, the rookie of the year, and the golden glove for the best defensive players by position are selected. Determining the winners of these awards and the resulting financial implications such as free agency, salary arbitration, and team payrolls (Haupert, 2007; Real, 2019) creates the need for an accurate ranking of baseball players.

In the game of baseball, as in all team sports, victory can only be achieved through the contribution and effort of all the players. Batting is one of the skills in baseball that arouses great passion, even more so because of how complicated it is. A sphere of 22.5 cm in circumference, weighing 149 g and capable of traveling at a speed of more than 90 mph must be struck with a bat no more than 1.07 m long and with a diameter of 7 cm at its thickest part. The ball, varying its trajectory in the air, covers the distance from the mound to home plate in about 0.42 s (Vistuer-Valdés, 1995). Because of this, the pitcher has a decisive and significant role in achieving success in a baseball game. A pitcher's main weapons are speed and control of his pitches, and the impact of these skills on his own team's performance and the decrease of the batting average of the opposing team has been studied (Chen & Chen, 2009; Gould & Winter, 2009). Pitchers are classified as starters and relievers. The starter is the player who starts the game and the goal is to keep him pitching for as many innings as possible. The reliever is the player who replaces the starter when his capabilities decrease or for strategic reasons that arise during the game (Chen et al., 2010).

As previously mentioned, the selection of award winners and the financial implications create the need to have performance-rating instruments for baseball players. The AHP method is a mathematical tool developed by Thomas Saaty in the 1980s aimed at obtaining the best decision from a series of values easily measurable by users (Saaty, 1980, 1990, 2008). Its flexibility and mathematical simplicity have resulted in it becoming a widely used decision making tool in various fields, such as the food industry, business, ecology, health, environment, and government (Vaidya & Kumar, 2006; Liberatore & Nydick, 2008; Panchal & Shrivastava, 2022; Veisi et al., 2022). In sports, it has been successfully applied with soccer, baseball, basketball, track and field, hockey, tennis, and American football (Nisel & Özdemir, 2016) and for evaluating the sports industry (Yong, 2021).

In this article, performance evaluation AHP models for baseball pitchers were developed, for starters and relievers. The research is the first of its kind using the AHP method to evaluate the global performance of baseball pitchers. Until now, the performance of pitchers has been assessed through Data Envelopment Analysis (Chen & Johnson, 2010) and using a combined AHP-TOPSIS model in the Chinese professional baseball league (Chen et al., 2014). Scala (2008) did not consider the problem of evaluating the performance of pitchers, but rather the substitution of relief pitchers during the game, taking into account factors such as handedness of the batter, the state of the game, the tiredness of the pitcher, and the pitchers available in the bullpen. The DEA and AHP-TOPSIS models evaluated the performance of the pitcher considering only his role and skills as a starting pitcher in the game. Conversely, the models proposed in this research

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aim to evaluate the overall performance of the pitcher, considering not only his performance as a pitcher but also his batting and fielding contributions and adapting these skills to the demands of the American and National MLB leagues. The main strength of the article is that it proposes a set of improvements to an existing methodology incorporating different types of indicators that help enhance the evaluation capacity of pitchers. Another fundamental contribution of the models is that they can be applied in a general way. That is, the work of the experts only involves the selection of the criteria and subcriteria and computation of their weights for the models. The experts are not necessary in the evaluation stage of the pitchers (alternatives) since the variables used are all numerical and the evaluation is carried out exclusively considering the standard performance statistics of each pitcher. This represents a significant difference from the AHP-TOPSIS model since that method uses the TOPSIS layer to rank the pitchers which makes it necessary to consult experts.

2. Fundamentals of the AHP

The AHP method is used to solve decision-making problems involving a finite set of alternatives and a goal. In order to decide on an organized way to generate priorities we need to decompose the decision into the following steps (Saaty, 2008).

1. Define the hierarchical structure of the problem from the top with the goal, the intermediate levels with the criteria and subcriteria, and at the bottom level the alternatives.
2. Construct a set of pairwise comparison matrices. Each element of a higher level is used to compare the elements in the level with respect to it, located immediately below.
3. Compute the consistency of the pairwise comparison matrices.
4. Use the priorities obtained from the comparisons to weight the priorities in the level immediately below. This should be done for every element. Then for each element in the level below add its weight values and obtain its overall priority. Continue this process of weighting and adding until the final priorities of the alternatives in the bottom level are obtained.

2.1 Step 1: Hierarchical structure

Figure 1 shows the hierarchical structure of the decision-making problem.

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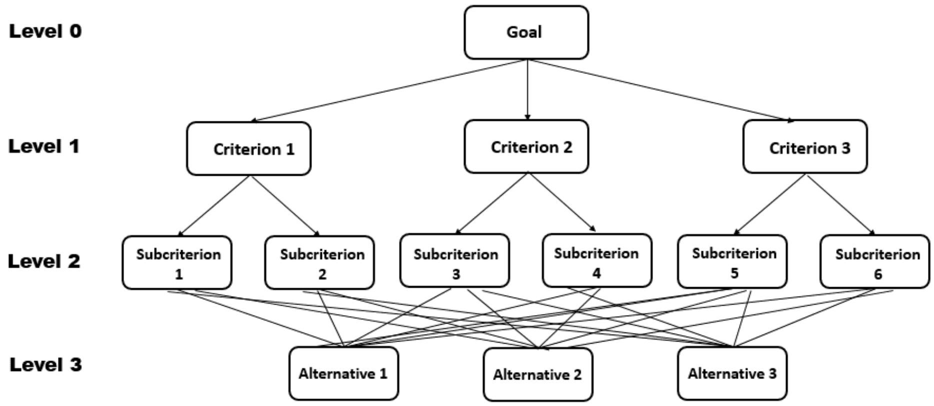

Figure 1 Decision-making problem hierarchy structure.

2.2 Step 2: Pairwise comparison matrix

If there are n criteria, $n(n-1)/2$ comparisons must be done. To make comparisons, a scale of numbers is used that indicates how many times one element is more relevant than another, about the criterion or property concerning which they are compared. Table 1 presents the numerical scale proposed by Saaty (1980) to establish the degrees of preference between the two items being compared. The comparisons are collected in the pairwise comparison matrix $\boldsymbol{A} = \left(a_{ij}\right)_{n\,x\,n}$ (Equation 1).

$$\boldsymbol{A} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \tag{1}$$

Where each element $a_{ij} > 0$ expresses the preference of criterion c_i over c_j. More precisely, according to Saaty's theory (1980), each element is supposed to be described as the quotient of two weights as seen in Equation (2).

$$a_{ij} \approx \frac{w_i}{w_j}\ \forall_{i,j} \tag{2}$$

This means that the matrix (Equation 1) is described by Equation (3):

$$\boldsymbol{A} = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} \tag{3}$$

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From where the condition of the multiplicative inverse results $a_{ij} = 1/a_{ji}\ \forall_{i,j}$ which allows us to rewrite the comparison matrix in the form of Equation (4).

$$\boldsymbol{A} = \begin{pmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{pmatrix} \tag{4}$$

this simplified structure of pairwise comparison matrices implies that if the criterion c_i has a *moderate importance* (see Table 1) concerning the criterion c_j, it follows that, $w_i/w_j = 3/1$ then it is deduced that the relation between c_j and c_i is $1/3$.

2.3 Step 3: Consistency results

A rational expert should formulate his preferences (Equation 2) exactly. This means that if one writes $a_{ij}a_{jk}$ and the condition $a_{ij} = w_i/w_j\ \forall\ i,j$ is applied, the following expression is deduced:

$$a_{ij}a_{jk} = \frac{w_i}{w_j}\frac{w_j}{w_k} = \frac{w_i}{w_k} = a_{ik}$$

That is, the following transitivity relation results as seen in Equation (5):

$$a_{ij}a_{jk} = a_{ik}\ \forall i,j,k \tag{5}$$

which means that every direct comparison a_{ik} is confirmed by an indirect comparison $a_{ij}a_{jk}\ \forall j$. A matrix that meets the transitivity condition is said to be consistent. Now, consistency is occasionally achieved. Despite the difficulty of determining a consistent comparison matrix, consistency is a highly desirable property. That is why certain violations of Equation (5) are tolerated through the definition of a consistency ratio given by Equation (6).

$$RC = CI/RI \tag{6}$$

with CI the consistency index given by $CI = (\lambda_{max} - n)/(n-1)$ with λ_{max} the maximum eigenvalue of matrix $\boldsymbol{A}$ and RI is the random index, which corresponds to an estimation of the average CI computed from a large set of randomly generated matrices of size n. In Table 2, estimated values of RI are reported (Alonso & Lamata, 2006). In practice, matrices with values $CR \leq 0.1$ are accepted and with values greater than 0.1 are rejected (Saaty, 1980).

Table 2
Values of RI (Alonso & Lamata, 2006)

$\boldsymbol{n}$	3	4	5	6	7	8	9	10
$\boldsymbol{RI}$	0.5247	0.8816	1.1086	1.2479	1.3417	1.4057	1.4499	1.4854

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2.4 Step 4: Priority vector

The last step is the computation of a priority vector for each pairwise comparison matrix. The normalized columns method was used in this research. First, all the columns need to be normalized so that the sum of all column values becomes one. Then, the arithmetic mean of the rows is taken and normalized to add up one to generate the weights.

3. Method

MLB comprises 30 teams, divided equally between the National League and the American League. The main difference between the leagues that were considered for this work is the American League's designated hitter rule. This rule allows a tenth player, a hitter who does not play in the field but bats regularly in place of the pitcher. Therefore, pitchers do not have to bat in the American League. That is why in the case of an American League pitcher, the model only considers the fielding aspect in addition to performance as a pitcher (starter or reliever). For the National League pitcher, the model evaluates three aspects to capture his overall performance, that is, pitching (starter or reliever) fielding and batting. Considering all of this data, four models were formed depending on the type of pitcher (starter or reliever) and the league where he plays (American or National). To construct these models, a team of five experts was formed. The experts all have many years of experience in baseball, as journalists, professional scouts, coaches, or players as can be seen in Table 3.

Table 3
Profile of the experts employed to develop the AHP models

Expert	Profile
1	International scout for the MLB Baltimore Orioles team for the region of Latin America, Mexico, and the Caribbean from 2011 to date.
2	Baseball coach with more than 25 years' experience in Venezuela and former minor league player with the *Leones del Caracas* team in Venezuela.
3	Scout for the Los Angeles Dodgers team assigned to the Dominican Republic specifically and the entire Latin American area. His experience in baseball began in 2012.
4	Sports journalist with more than 40 years of experience writing for the newspapers *El Nacional* and *El Emergente* in Venezuela.
5	Former minor league player for the Baltimore Orioles team in the US and Margarita Braves in Venezuela. He played catcher for both organizations and played up to the Rookie League in the Florida Gulf Coast League.

Table 4 describes the different baseball statistics used in the models. Figures 2, 3, 4, and 5 show the hierarchical structures with their priority weights for the four models of pitchers according to their type and league they play in. The weights were obtained by applying the AHP methodology and using the method of aggregation of individual judgments (Forman & Peniwati, 1998; Ossadnik, 2016) to aggregate the five different

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pairwise comparison matrices for each expert into a single matrix $\boldsymbol{A}^G = \left(a_{ij}^G\right)$ using the geometric mean, and then the priority vector be calculated through the normalization column method.

Table 4
Baseball statistics used to evaluate the overall performance of pitchers

Stat	**Description**	**Equation**
Fld	Fielding average	$Fld = (O + A)/(O + A + E)$ $O: Outs, A: Assists, E: Errors$
$Fld/\ lgFld$	Fielding average of the player with respect to the league	$Fld/\ lgFld$ $lg\ Fld$:league fielding average
ERA	Earned run average	$ERA = (9 * ER)/IP$ $ER: earned\ run$ $IP: Innings\ pitched$
$WHIP$	Walks and hits per innings pitched	$WHIP = (BB + H)/IP$ $H: Hits$ $BB: A\ walk\ (or\ base\ on\ ball)$
AVE	Batting average against the pitcher or opponents' batting average	$AVE = H/AB$ $AB: At\ bat$
P/IP	Pitches per innings pitched	P/IP $P: Pitches$
$W - L$	Pitcher's winning average	$W - L\ = W/(W + L)$ $W: Wins, L: Loss$
$S - OS$	Saved average	S/OS $S: Saved, SO: Saved\ opportunity$
AVG	Batting average of the pitcher	$AVG = H/AB$
OBP	On-base percentage	$OBP = \dfrac{H + BB + HBP}{AB + BB + HBP + SF}$ $HBP: Hit - by - pitch$ $SF: Sacrifice\ Fly$
SLG	Slugging	*SLG* = (*H* + 2**2B* + 3**3B* + 4**HR*)/*AB* *2B*: Double, *3B*; Triple, *HR*: Homerun

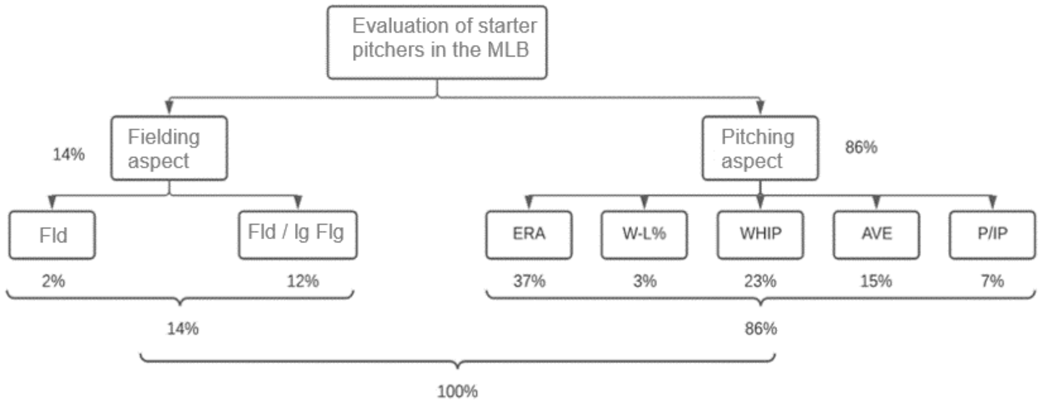

Figure 2 Model 1 for a starting pitcher in the American League.

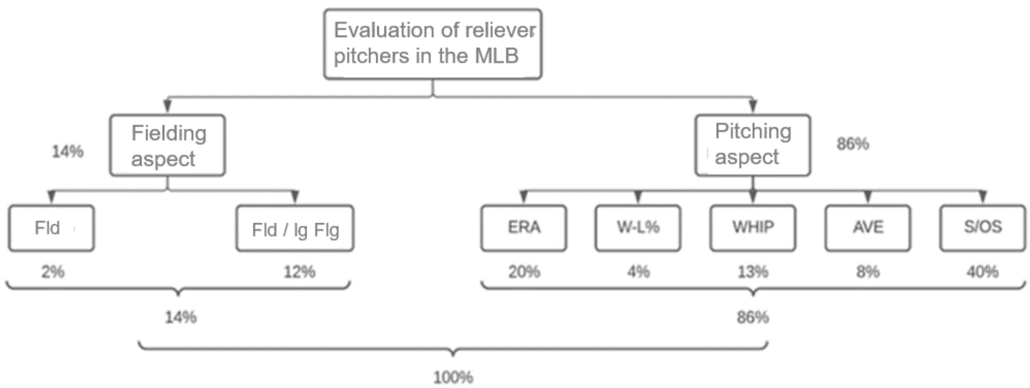

Figure 3 Model 2 for a relief pitcher in the American League

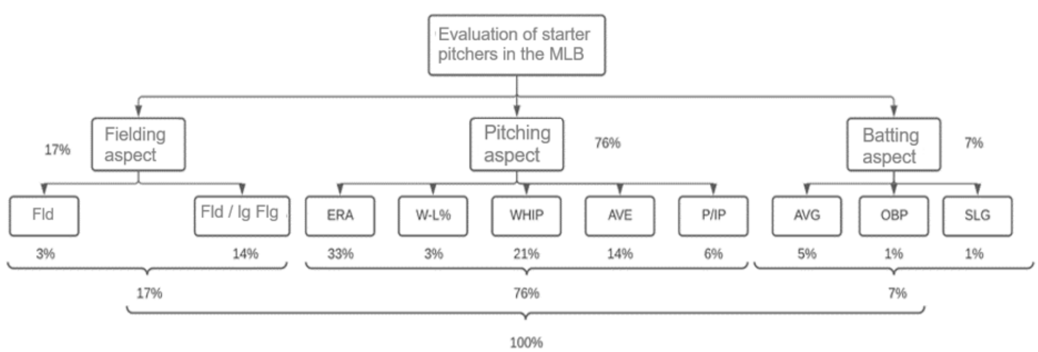

Figure 4 Model 3 for a starting pitcher in the National League

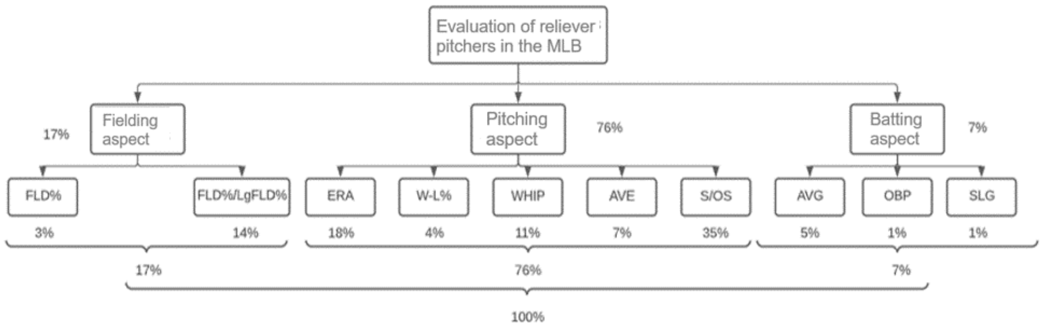

Figure 5 Model 4 for a relief pitcher in the National League

Next, we explore the procedure for obtaining the different weights for the models. Only model 1 shown in Figure 2 will be considered as an example. To determine the weights of the criteria level, surveys were given to the five experts. Expert 1 responded as indicated in Figure 6 from which we obtain the following pairwise comparison matrix (Equation 7).

$$\boldsymbol{A_1} = \begin{pmatrix} 1 & 0.2 \\ 5 & 1 \end{pmatrix} \tag{7}$$

Applying a similar procedure, the pairwise comparison matrices of the remaining experts were computed resulting in Equation (8).

$$\boldsymbol{A_2} = \begin{pmatrix} 1 & 0.167 \\ 6 & 1 \end{pmatrix}, \boldsymbol{A_3} = \begin{pmatrix} 1 & 0.143 \\ 7 & 1 \end{pmatrix}, \boldsymbol{A_4} = \begin{pmatrix} 1 & 0.2 \\ 5 & 1 \end{pmatrix}, \boldsymbol{A_5} = \begin{pmatrix} 1 & 0.143 \\ 7 & 1 \end{pmatrix} \tag{8}$$

	9	**7**	**5**	**3**	**1**	**3**	**5**	**7**	**9**	
Fielding							**X**			Pitching

Figure 6 Survey given to Expert 1 to assess his preference at the criteria level of model 1

These matrices were combined into a single matrix by calculating the geometric mean. Then, the overall resulting matrix was normalized through column summation and the priority vector was obtained by computing the average of the rows of the normalized matrix. The operations can be seen in Table 5.

Table 5
Final priority vector obtained at the criteria level for model 1

Overall pairwise comparison matrix (geometric mean)		**Column normalization**		**Priority weight**
1	0.17	0.14	0.14	0.14
6	1	0.86	0.86	0.86

To understand how to work at the subcriteria level of model 1, we show how the weights of the fielding average (Fld) and the fielding average of the player with respect to the league ($Fld\ /\ lgFld$) were obtained After consulting the five experts and aggregating their pairwise comparison matrices through the geometric mean, the results of Table 6 were attained.

Table 6
Secondary weights of the subcriteria level of model 1 for the fielding criterion

Overall pairwise comparison matrix (geometric mean)		**Column normalization**		**Priority weight**
1	0.2	0.167	0.167	0.167
5	1	0.833	0.833	0.833

Finally, the weights of the subcriteria level of model 1 for the fielding criterion $(0.167, 0.833)^T$ were multiplied by the weight of the fielding criterion (0.14) yielding $(0.02, 0.12)^T$. These weights indicate how the relative importance of 14% for the fielding criterion is distributed within the two defensive subcriteria. By repeating this procedure, the remaining weights of model 1 could be obtained, as well as any of the other three models.

4. Results

Next, we evaluated the different hierarchical models of pitchers through four tests. In the first and second tests, the three finalist starters from both the American League and the National League were ranked using Model 1 and Model 3, respectively for the 2018, 2019, 2020, 2021, and 2022 Cy Young Award. In the third, the three finalist relievers for the 2017 Trevor Hoffman Award were ranked employing Model 4, and finally, in the fourth test, the three finalist relievers for the 2017 Mariano Rivera Award were evaluated employing Model 2. All the performance statistics for the pitchers were obtained from the MLB and the sports TV network ESPN websites.

4.1 Cy Young Award (American League)

The Cy Young Award is given annually to the best pitchers in MLB, one each for the American League and the National League (The Official Site of Major League Baseball a).

We developed this first result on the application of the proposed models in more detail; however, the following ones, being very similar from the point of view of the steps of the procedure, were treated more briefly.

The three finalists for the Cy Young Award during the 2018 American League season were the starting pitchers, Justin Verlander, Blake Snell and Corey Kluber. Model 1 was used for performance ranking and the statistics of the pitchers during that year appear in Table 7.

Table 7
Performance statistics for the three finalist starter pitchers for Cy Young Award during season 2018.

	$\boldsymbol{ERA}$	$\boldsymbol{AVE}$	$\boldsymbol{WHIP}$	$\boldsymbol{W-L}$	$\boldsymbol{Fld/lgF}$	$\boldsymbol{P/IP}$	$\boldsymbol{Fld}$
Justin Verlander	2.52	0.200	0.90	0.64	0.965	16.01	0.95
Blake Snell	1.89	0.178	0.97	0.81	0.965	16.15	0.95
Corey Kluber	2.89	0.223	0.99	0.74	1.016	14.80	1.00

Note: Pitcher statistics were collected from https://www.mlb.com/ and https://www.espn.com/mlb/

Since $ERA, WHIP, AVE$ and P/IP statistics are inverse (a better result corresponds to a lower number), they must be transformed into a direct equivalent to use them within the AHP. To this end, the worst results during the year 2018 for these statistics were determined and then the real statistics (pitcher performance) were subtracted from these values in order to obtain the direct equivalent. The worst results were $ERA = 6.13, WHIP = 1.48, AVE = 0.280$ and $P/IP = 18.72$. After normalizing each column by dividing by the sum of the values in that column and multiplying by the vector of weights of the subcriteria level of model 1, the results are shown in Table 8. It is very important to keep in mind that this simple normalization allows the computation of all the priority vectors at the subcriteria level and in this way, one of the typical steps of the AHP method, the consultation of experts to evaluate the alternatives is not required in our model.

Table 8
Results of applying Model 1 to the 2018 AL Cy Young Award finalist starters

	Fld	Fld/lg Fld	ERA	W – L	WHIP	AVE	P/IP
Justin Verlander	0.3276	0.3276	0.3255	0.2924	0.3671	0.3347	0.2946
Blake Snell	0.3276	0.3276	0.3823	0.3691	0.3228	0.4268	0.2793
Corey Kluber	0.3448	0.3448	0.2922	0.3385	0.3101	0.2385	0.4261

*

Weights at the subcriteria level (model 1)	
Fld	0.02
Fld/lgFld	0.12
ERA	0.37
W – L	0.03
WHIP	0.23
AVE	0.15
P/IP	0.07

=

	Overall priority vector
Justin Verlander	0.334
Blake Snell	0.360
Corey Kluber	0.306

Note: Pitcher statistics were collected from https://www.mlb.com/ and https://www.espn.com/mlb/

The best alternative given by the model was the pitcher Blake Snell who was the actual 2018 American League Cy Young Award winner. Table 9 shows the results obtained (overall priority vectors) by applying model 1 to the finalists for the American League Cy Young Award for the 2019, 2020, 2021 and 2022 seasons. In all cases, the player with the highest weight value computed by the model was the winner of the award.

Table 9
Results of applying Model 1 to the 2019, 2020, 2021, and 2022 AL Cy Young Award finalist starters.

2019	Overall priority vector	2020	Overall priority vector	2021	Overall priority vector	2022	Overall priority vector
Justin Verlander	0.368	**Shane Bieber**	0.368	**Gerrit Cole**	0.321	**Justin Verlander**	0.390
Gerrit Cole	0.350	**Kenta Maeda**	0.346	**Lance Lynn**	0.329	**Dylan Cease**	0.279
Charlie Norton	0.283	**Hyun-Jin Ryu**	0.286	**Robbie Ray**	0.349	**Alek Manoah**	0.331

4.2 Cy Young Award (National League)

After converting the inverse variables into direct equivalents and carrying out the normalization by columns of the statistics of the finalist starters of the National League for the Cy Young Award for the 2018 season, the results of the application of model 3 are shown in Table 10.

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Table 10
Priority vectors resulting for each subcriteria in Model 3 for finalist starters for 2018 NL Cy Young Award

	Fld	**Fld/lg Fld**	**WHIP**	**W-L**	**ERA**	**P/IP**	**AVE**	**SLG**	**OBP**	**AVG**
Jacob deGrom	0.338	0.338	0.345	0.265	0.376	0.377	0.324	0.163	0.189	0.185
Max Scherzer	0.325	0.325	0.345	0.363	0.305	0.278	0.355	0.246	0.246	0.274
Aaron Nola	0.336	0.336	0.309	0.372	0.319	0.345	0.320	0.591	0.565	0.541

Note: Pitcher statistics were collected from https://www.mlb.com/ and https://www.espn.com/mlb/

Next, we collected the results from Table 10 into a matrix, and multiplied it by the vector of weights at the level of subcriteria of Model 3. The priority vector $(0.3398, 0.3200, 0.3396)^T$ was obtained, which indicates that the alternative that globally satisfies all the criteria and subcriteria in Model 3 (although very narrowly) corresponds to the starting pitcher Jacob deGrom who was the actual winner of the Cy Young Award for the National League in 2018. Table 11 shows the results obtained (overall priority vectors) by applying Model 3 to the finalists for the National League Cy Young Award for the 2019, 2020, 2021 and 2022 seasons. With the exception of the 2022 season where the winner was Sandy Alcantara, in all other seasons the player with the highest weight value computed by the model won the award.

Table 11
Results of applying Model 1 to the 2019, 2020, 2021, and 2022 NL Cy Young Award finalist starters

2019	**Overall priority vector**	**2020**	**Overall priority vector**	**2021**	**Overall priority vector**	**2022**	**Overall priority vector**
Jacob deGrom	0.349	**Trevor Bauer**	0.364	**Corbin Burnes**	0.355	Sandy Alcantara	0,341
Hyun-Jin Ryu	0.340	**Jacob deGrom**	0.308	**Zach Wheeler**	0.306	Max Fried	0,309
Max Scherzer	0.310	**Yu Darvish**	0.328	**Max Scherzer**	0.339	Julio Urias	0,350

4.3 Trevor Hoffman Award 2017 (National League)

The Trevor Hoffman Award has been awarded to the best reliever in the National League since 2014 (The Official Site of Major League Baseball b). Following the conversion of the inverse variables into direct equivalents (Worst statistics of 2017: $ERA = 5.52, WHIP = 1.54, AVE = 0.308$) and normalizing the performance statistics of the three finalist relievers of the National League for the Trevor Hoffman Award for the 2017 season, the results of the application of model 4 are shown in Table 12.

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Table 12
Priority vectors resulting for each subcriteria in Model 4 for finalist starters for 2017 NL Trevor Hoffman Award

	Fld	**Fld/lg Fld**	**W-L**	**WHIP**	**ERA**	**AVE**	**S/OS**	**SLG**	**OBP**	**AVG**
Wade Davis	0.337	0.337	0.357	0.255	0.289	0.320	0.345	0.000	0.000	0.000
Kenley Jansen	0.325	0.325	0.536	0.503	0.376	0.344	0.347	1.000	1.000	1.000
Corey Knebel	0.338	0.338	0.107	0.242	0.335	0.336	0.308	0.000	0.000	0.000

Note: Pitcher statistics were collected from https://www.mlb.com/ and https://www.espn.com/mlb/

After forming a matrix with the results of Table 12 and multiplying it by the vector of weights $(0.03, 0.14, 0.18, 0.04, 0.11, 0.07, 0.35, 0.05, 0.01, 0.01)^T$ corresponding to the subcriteria level of model 4, the priority vector $(0.30, 0.42, 0.28)^T$, was obtained which indicates that the choice that comprehensively satisfies all the attributes corresponds to reliever Kenley Jansen, who was the actual winner of the Trevor Hoffman Award for the National League in 2017.

4.4 Mariano Rivera Award 2017 (American League)

The Mariano Rivera American League Reliever of the Year Award was introduced by MLB in 2014 (The Official Site of Major League Baseball b). Following the conversion of the inverse variables into direct equivalents and normalizing the performance statistics of the three finalist relievers of the American League for the Mariano Rivera Award for the 2017 season, the results of the application of Model 2 are shown in Table 13.

Table 13
Priority vectors resulting for each subcriteria in Model 2 for finalist starters for 2017 AL Mariano Rivera Award

	Fld	**Fld/lgFld**	**W-L**	**ERA**	**WHIP**	**S/OS**	**AVE**
Ken Giles	0.321	0.321	0.290	0.293	0.326	0.355	0.305
Craig Kimbrel	0.357	0.357	0.390	0.337	0.374	0.336	0.356
David Robertson	0.321	0.321	0.319	0.335	0.300	0.328	0.339

Note: Pitcher statistics were collected from https://www.mlb.com/ and https://www.espn.com/mlb/

After constructing the matrix with the priority vectors from Table 13, and multiplying it by the vector of weights of the subcriteria level of Model 2, the priority vector $(0.31, 0.36, 0.33)^T$ was obtained, which indicates that the choice that globally satisfies all the attributes corresponds to the reliever Craig Kimbrel who was the actual winner of the Mariano Rivera award for the National League in 2017.

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5. Discussion and conclusion

This work provides an additional mathematical analysis for the evaluation of sports performance, particularly in the selection of professional baseball pitchers. This is a difficult task for managers and coaches and can be defined as a multi-criteria decision-making.

Different AHP models were formulated to evaluate the performance of pitchers in their roles as starters or relievers depending on the MLB League they play in. The models use widely known baseball statistics to evaluate the overall performance of pitchers. The statistics are quite similar when evaluating the starter or the reliever. The fundamental difference is that for the first, the pitches per inning was considered to indirectly provide information about the pitcher's fatigue; while for the second, the save average gives a measure of the pitcher's success as a reliever. The models evaluate overall performance because, in addition to pitching, they take into account the pitcher's contribution of fielding and batting.

The models were applied to different emblematic MLB awards and the results produced by the models were consistent with the pitchers that actually won the awards. An important result is the general scope of the models. Although it is necessary to have a team of experts to determine the relative importance of the criteria and sub-criteria levels of the hierarchy structure, their contribution is not required to evaluate the pitchers (alternatives). This is because at the sub-criteria level there are only numerical variables corresponding to the performance results obtained by each pitcher. This allows the vector of weights for each sub-criterion to be easily computed by normalizing by the sum of columns.

The models can not only be used as an instrument to determine the winner of an award, but also to allow managers and coaches to make decisions regarding the selection of pitchers on their roster. The models can evaluate the performance of pitchers in a single season as well as be used to evaluate a pitcher's career and decide, for example, if it is sufficiently meritorious to enter the Baseball Hall of Fame. Finally, even if the models were intended for use in the United States MLB, they are general enough to be adapted to any professional baseball league.

REFERENCES

Alonso, J. and Lamata, M. (2006). Consistency in the analytic hierarchy process: a new approach. *International Journal of Uncertainty, Fuzziness and Knowledge based Systems*, 14(4), 445-459. https://doi.org/10.1142/S0218488506004114

Chen, C. and Chen, T. (2009). Starting pitchers' skills positioning of CPBL in 2008. *Journal of Physical Education*, 8, 109-125.

Chen, W. and Johnson, A. (2010). The dynamics of performance space of MLB pitchers. *Annals of Operations Research*, *181*(1), 287-302. http://dx.doi.org/10.1007/s10479-010-0743-9

Chen, C., Lin, M., Lee, Y., Chen, T. and Tseng, C. (2010). Best starting pitcher of the Chinese Professional Baseball League in 2009. *World Academy of Science, Engineering and Technology 2010*, 72, 210-212. https://doi.org/10.1007/978-3-642-27552-4_86

Chen, C., Lee, Y. and Tsai, C. (2014) Professional baseball team starting pitcher selection using AHP and TOPSIS methods, *International Journal of Performance Analysis in Sport*, *14*(2), 545-563. https://doi.org/10.1080/24748668.2014.11868742

Forman, E., and Peniwati, K. (1998). Aggregating individual judgments and priorities with the analytic hierarchy process. *European Journal of Operational Research*, *108*(1), 165-169. https://doi.org/10.1016/S0377-2217(97)00244-0

Gould, E. and Winter, E. (2009). Interaction between worker and the technology of production: evidence from professional baseball. *The Review of Economics and Statistics*, *91*(1), 188-200. https://doi.org/10.1162/rest.91.1.188

Haupert, M. J. (2007) Bonus clauses and the standard player contract. *The Baseball Research Journal*, 36, 109-116.

Lee, Y. H. (2018). Common factors in Major League Baseball game attendance. *Journal of Sports Economics*, *19*(4), 583-598. https://doi.org/10.1177/1527002516672061

Liberatore, M. J., and Nydick, R. L. (2008). The analytic hierarchy process in medical and health care decision making: A literature review. *European Journal of Operational Research*, *189*(1), 194-207. https://doi.org/10.1016/j.ejor.2007.05.001

Nisel, S., and Özdemir, M. (2016). Analytic hierarchy process & analytic network process in sport: a comprehensive literature review. *International Journal of the Analytic Hierarchy Process*, *8*(3), 405-429. https://doi.org/10.13033/ijahp.v8i3.448

Ossadnik, W., Schinke, S., and Kaspar, R. H. (2016). Group aggregation techniques for analytic hierarchy process and analytic network process: a comparative analysis. *Group Decision and Negotiation*, 25, 421-457. https://doi.org/10.1007/s10726-015-9448-4

Panchal, S., and Shrivastava, A. K. (2022). Landslide hazard assessment using analytic hierarchy process (AHP): A case study of National Highway 5 in India. *Ain Shams Engineering Journal*, *13*(3), 1016-26. https://doi.org/10.1016/j.asej.2021.10.021

Powers, A. T. (2015). *The business of baseball*. Jefferson, NC: McFarland and Co. Inc.

Real, A. (2019). The advantages of incorporating mechanisms from the salary arbitration models of MLB and the NHL in a salary arbitration system in MLS. *Pepperdine. Dispute Resoution Journal*, *19*(1), 1-17.

Saaty, T. (1980). *The Analytic Hierarchy Process*. New York: McGraw Hill International.

Saaty, T. (1990). How to make a decision: The Analytic Hierarchy Process. *European Journal of Operational Research*, 48, 9-26. https://doi.org/10.13128/Aestimum-7138

Saaty, T. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences 1*(1), 83-98. https://doi.org/10.1504/IJSSCI.2008.017590

Scala, N. M. (2008). Decision modeling and applications to Major League Baseball pitcher substitution. In *29th Annual National Conference of the American Society for Engineering Management 2008, ASEM 2008* (pp. 212-217). Pittsburgh, PA: University of Pittsburgh.

The Official Site of Major League Baseball (a) (n.d.). *Inside MLB Awards: Cy Young*. https://www.mlb.com/awards/cy-young

The Official Site of Major League Baseball (b) (n.d.). *Relievers of the Year*. https://www.mlb.com/awards/reliever-of-the-year

Vaidya, O. S., and Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research*, *169*(1), 1-29. https://doi.org/10.1016/j.ejor.2004.04.028

Veisi, H., Deihimfard, R., Shahmohammadi, A., and Hydarzadeh, Y. (2022). Application of the analytic hierarchy process (AHP) in a multi-criteria selection of agricultural irrigation systems. *Agricultural Water Management*, 267, 107619. https://doi.org/10.1016/j.agwat.2022.107619

Vistuer-Valdés, J. (1995). *Béisbol. La acción de batear*. Playa, Cuba: Editorial Científico-Técnica.

Yong, W. (2021, March). Analytic Hierarchy Process and intelligent evaluation of regional sports economic data. In *2021 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*. https://doi.org/10.1109/ICITBS53129.2021.00098