Identification of NBA Most Valuable Player Candidates Using Singular Value Decomposition

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***Abstract*— The 2025–2026 NBA season has started, and players are competing to become the Most Valuable Player (MVP). This study aims to identify strong MVP candidates using Singular Value Decomposition (SVD) applied to NBA player statistics. Player data, including points, rebounds, assists, steals, blocks, and other performance metrics, are organized into a matrix and normalized using Z-score standardization to ensure fair comparison across features. The matrix is then decomposed into U, S, and Vt matrices to reveal underlying patterns of player performance. By analyzing the contributions of each player to these patterns, a composite score is calculated to rank potential MVP candidates. Results using the 2024–2025 season data show that top statistical performers, such as Nikola Jokić and Shai Gilgeous-Alexander, align well with real-life MVP results, validating the method. Applying the same methodology to the 2025–2026 season allows the identification of top candidates based purely on statistical performance. This study demonstrates that SVD is an effective, data-driven tool for evaluating player performance and highlighting potential MVP candidates, providing insights into both historical and current NBA seasons.**

***Keywords*—SVD, NBA, MVP, Candidates.**

I. Introduction

The 2025–2026 NBA season has officially started, creating excitement as many players aim to become superstars, while rising stars try to prove themselves in the league. Besides personal achievements, these players compete for one of the highest individual awards in basketball, the NBA Most Valuable Player (MVP) award.

During the season, players show strong performances in many statistical categories, such as points per game (PPG), assists, rebounds, steals, blocks, and overall efficiency. However, only one player can be chosen as the MVP, which makes the selection process very competitive. The MVP decision is often influenced not only by statistics, but also by team performance, media opinions, and popular narratives. As a result, the selection can be subjective and sometimes inconsistent.

By using player statistical data, strong candidates for the NBA Most Valuable Player (MVP) award can be analyzed. This data contains many variables, such as points, assists, rebounds, steals, and blocks, which makes it high-dimensional. Each of these statistics has a strong relationship with how valuable a player is to their team and their chances of becoming MVP.

However, the MVP selection is not based only on recorded statistics. There are other factors, such as leadership, team success, and game impact, that are difficult to represent directly in numerical data. Because of this, analyzing MVP candidates using raw statistics alone can be inefficient and may not show the overall contribution of a player clearly.

Therefore, this paper aims to study the use of Singular Value Decomposition (SVD) as a mathematical and statistical approach to identify potential NBA MVP candidates. SVD helps reduce the complexity of high-dimensional data while keeping the most important information. By applying SVD to player statistics, this study seeks to provide a clearer and more objective way to evaluate player performance and highlight players who have a strong overall impact in the NBA.

II. Theoretical Framework

2.1. Matrix

A matrix with size M × N is a matrix that has M rows and N columns.

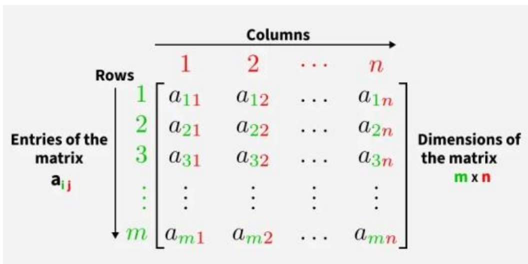


Fig. 2.1.Matrix M x N
Source : https://www.geeksforgeeks.org/maths/introduction-to-matrices/ (accessed Dec 23, 2025).

The size of the matrix itself is called as an order, If the m and the n have the same value, the matrix will be called a square matrix with the value of order n.

A matrix with size N × N has a diagonal called the main diagonal. In contrast, a matrix with size M × N does not have a main diagonal.

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$

Fig. 2.2.Matrix N x N with main diagonal
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-01-Review-Matriks-2025.pdf (accessed Dec 23, 2025).

1. Matrix Addition/Subtraction

A matrix has the property of addition. If there are two matrices, the addition is performed by adding the elements that are in the same row and column positions. For example, if matrix C is the result of adding matrices A and B, then each element Cij is obtained from Aij + Bij.

$$A+B=\begin{bmatrix} -2 & 4 & 5 & 4 \\ 1 & 2 & 2 & 3 \\ 7 & 0 & 3 & 5 \end{bmatrix}, \quad A-B=\begin{bmatrix} 6 & -2 & -5 & 2 \\ -3 & -2 & 2 & 5 \\ 1 & -4 & 11 & -5 \end{bmatrix}$$

Fig. 2.3.Matrix Addition/Substraction
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-01-Review-Matriks-2025.pdf (accessed Dec 23, 2025).

Matrix subtraction follows the same rule as matrix addition. The subtraction is performed by subtracting the elements that are in the same row and column positions. For example, if matrix C is the result of subtracting matrix B from matrix A, then each element Cij is obtained from Aij − Bij.

2. Matrix Multiplication

Matrix multiplication is divided into two types: multiplication between two matrices and multiplication of a matrix by a scalar. Multiplying a matrix by a scalar is done by multiplying the scalar value with each element in the matrix. For example, if a scalar value c is multiplied by a matrix M, then each element Mij in the matrix becomes cMij.

$$A=\begin{bmatrix} 2 & 3 & 4 \\ 1 & 3 & 1 \end{bmatrix},$$

$$2A=\begin{bmatrix} 4 & 6 & 8 \\ 2 & 6 & 2 \end{bmatrix},$$

Fig. 2.4.Multiplication Scalar
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-01-Review-Matriks-2025.pdf (accessed Dec 23, 2025).

Then, there is multiplication between two matrices. This multiplication is done by multiplying each row of the first matrix with each column of the second matrix and then adding the results. For example, if matrices A and B are multiplied to produce matrix C, there is a special rule that must be followed: the number of columns in matrix A must be the same as the number of rows in matrix B. If matrix A has an order of m × n and matrix B has an order of n × p, then the resulting matrix C will have an order of m × p. In this process, each row in matrix A is multiplied with each column in matrix B, and the results are summed to form the elements of matrix C.

$$\mathbf{A}=\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}, \quad \mathbf{B}=\begin{pmatrix} b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{np} \end{pmatrix}$$

$$\mathbf{C}=\begin{pmatrix} a_{11}b_{11}+\cdots+a_{1n}b_{n1} & a_{11}b_{12}+\cdots+a_{1n}b_{n2} & \cdots & a_{11}b_{1p}+\cdots+a_{1n}b_{np} \\ a_{21}b_{11}+\cdots+a_{2n}b_{n1} & a_{21}b_{12}+\cdots+a_{2n}b_{n2} & \cdots & a_{21}b_{1p}+\cdots+a_{2n}b_{np} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1}b_{11}+\cdots+a_{mn}b_{n1} & a_{m1}b_{12}+\cdots+a_{mn}b_{n2} & \cdots & a_{m1}b_{1p}+\cdots+a_{mn}b_{np} \end{pmatrix}$$

Fig. 2.5.A Multiplication B
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-01-Review-Matriks-2025.pdf (accessed Dec 23, 2025).

3. Transpose Matrix

Matrix transpose is an operation performed by exchanging the elements in a matrix, where the element mij is swapped with the element mji. If a matrix has an order of m × n, after the transpose operation it will change to an order of n × m. For example, a matrix A has a transpose matrix AT, which contains the exchanged elements.

$$A=\begin{bmatrix} 1 & -2 & 4 \\ 3 & 7 & 0 \\ -5 & 8 & 6 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -2 & 4 \\ 3 & 7 & 0 \\ -5 & 8 & 6 \end{bmatrix} \rightarrow A^T=\begin{bmatrix} 1 & 3 & -5 \\ -2 & 7 & 8 \\ 4 & 0 & 6 \end{bmatrix}$$

Fig. 2.6.Transpose A
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-01-Review-Matriks-2025.pdf (accessed Dec 23, 2025).

2.2. Matrix Decomposition

Matrix can be decomposed using many methods. However, in this study, only three types of decomposition are used, namely LU decomposition, QR decomposition, and Singular Value Decomposition (SVD).

1. LU Decomposition

LU decomposition is a way to factor a matrix A into two parts, namely L and U, so that the equation A = LU is formed. There is two methods for decomposing the matrix, as follows.

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}}_{A} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ l_{21} & 1 & 0 & 0 \\ l_{31} & l_{32} & 1 & 0 \\ l_{41} & l_{42} & l_{43} & 1 \end{bmatrix}}_{L} \times \underbrace{\begin{bmatrix} u_{11} & u_{12} & u_{13} & u_{14} \\ 0 & u_{22} & u_{23} & u_{24} \\ 0 & 0 & u_{33} & u_{34} \\ 0 & 0 & 0 & u_{44} \end{bmatrix}}_{U}$$

Fig. 2.7. LU Decomposition
Source :
https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-21-Singular-value-decomposition-Bagian1-2025.pdf (accessed Dec 23, 2025).

2. QR Decomposition

QR decomposition is a technique used to factor an m × n matrix into two matrices, Q and R. In the equation A = QR, matrix Q is an orthonormal matrix, and matrix R is an upper triangular matrix. One method used to obtain matrices Q and R is the Gram–Schmidt method. This method treats matrix A as a collection of column vectors, from a1 to an. Through a specific calculation process, matrices Q and R are obtained so that the QR decomposition is formed.

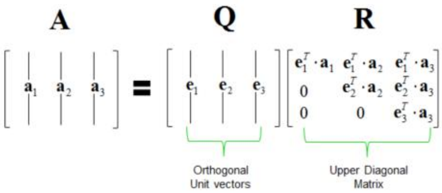


Fig. 2.8.QR Decomposition
Source : https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-21-Singular-value-decomposition-Bagian1-2025.pdf (accessed Dec 23, 2025).

3. Singular Value Decomposition (SVD)
If there is a matrix A with rank k and order m × n, then the matrix can be decomposed as follows:

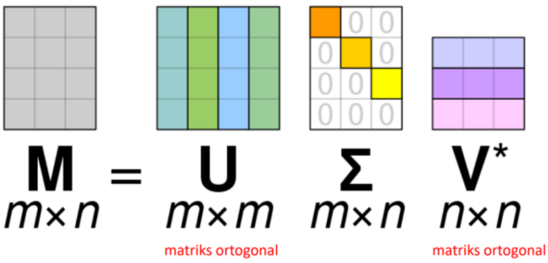
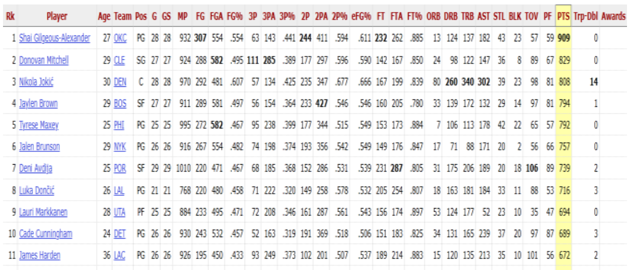


Fig. 2.9.Singular Value Decomposition (SVD)
Source : https://informatika.stei.itb.ac.id/~rinaldi.munir/AljabarGeometri/2025-2026/Algeo-21-Singular-value-decomposition-Bagian1-2025.pdf (accessed Dec 23, 2025).

2.3. Statistic NBA

NBA player statistics are used to measure individual player performance during a season. These statistics provide numerical data that describe how a player contributes to the game.

Some common NBA player statistics include points (PTS), rebounds (REB), assists (AST), steals (STL), blocks (BLK), field goal percentage (FG%), and turnovers (TOV). Each of these statistics represents a different aspect of a player's performance, such as scoring ability, teamwork, defensive contribution, and efficiency.



Rk	Player	Age	Team	Pos	G	GS	MP	FG	FGA	FG%	3P	3PA	3P%	2P	2PA	2P%	eFG%	FT	FTA	FT%	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS	Trp-Dbl	Awards
1	Shai Gilgeous-Alexander	27	OKC	PG	28	28	932	**307**	554	.554	63	143	.441	**244**	411	.594	.611	**232**	262	.885	13	124	137	182	43	23	57	59	**909**	0	
2	Donovan Mitchell	29	CLE	SG	27	27	924	288	**582**	.495	**111**	**285**	.389	177	297	.596	.590	142	167	.850	24	98	122	147	36	8	89	67	829	0	
3	Nikola Jokić	30	DEN	C	28	28	970	292	481	.607	57	134	.425	235	347	.677	.666	167	199	.839	80	**260**	**340**	**302**	39	23	98	81	808	**14**	
4	Jaylen Brown	29	BOS	SF	27	27	911	289	581	.497	56	154	.364	233	**427**	.546	.546	160	205	.780	33	139	172	132	29	14	97	81	794	1	
5	Tyrese Maxey	25	PHI	PG	25	25	995	272	**582**	.467	95	238	.399	177	344	.515	.549	153	173	.884	7	106	113	178	42	22	65	57	792	0	
6	Jalen Brunson	29	NYK	PG	26	26	916	267	554	.482	74	198	.374	193	356	.542	.549	149	176	.847	17	71	88	171	20	2	56	66	757	0	
7	Deni Avdija	25	POR	SF	29	29	1010	220	471	.467	68	185	.368	152	286	.531	.539	231	**287**	.805	31	175	206	189	20	18	**106**	89	739	2	
8	Luka Dončić	26	LAL	PG	21	21	768	220	480	.458	71	222	.320	149	258	.578	.532	205	254	.807	18	163	181	184	33	11	88	53	716	3	
9	Lauri Markkanen	28	UTA	PF	25	25	884	233	495	.471	72	208	.346	161	287	.561	.543	156	174	.897	53	124	177	52	23	10	35	47	694	0	
10	Cade Cunningham	24	DET	PG	26	26	930	243	532	.457	52	163	.319	191	369	.518	.506	151	183	.825	34	131	165	239	37	20	97	87	689	3	
11	James Harden	36	LAC	PG	26	26	926	195	450	.433	93	249	.373	102	201	.507	.537	189	214	.883	15	120	135	213	35	10	101	56	672	2	

Fig. 2.10.Table Statistic Of NBA Player

Source : https://www.basketball-reference.com/leagues/NBA_2026_totals.html (accessed Dec 23, 2025).

The main purpose of using NBA player statistics is to provide a quantitative representation of player performance. These statistics also serve as the basic data for mathematical and statistical analysis in this study.

NBA player statistics are numerical data that represent the individual performance of players over one competition season.

2.4. Data Normalization (Standardization)

The formula below is used for data normalization, also known as standardization or Z-score normalization:

$$X\_normalized = (X - mean) / std$$

Data normalization is an important step in data analysis, especially when working with statistical data that has different value ranges. One common normalization method is standardization, also known as Z-score normalization. This method transforms the data so that each statistical feature has a mean value of zero and a standard deviation of one. By doing this, the data becomes unitless and easier to compare across different variables.

In the context of NBA player statistics, different statistics have very different scales. For example, points per game usually have much larger values compared to rebounds or field goal percentage. If the data is not normalized, statistics with larger numerical values can dominate the analysis and affect the results of mathematical methods such as Singular Value Decomposition (SVD). Therefore, normalization is applied to ensure that each statistic contributes fairly to the analysis, allowing SVD to capture the overall performance patterns of players more accurately.

III. Method

3.1. Data preparation

Before performing the SVD analysis, a data preparation process is carried out on the NBA player statistics on 2024-2025. The original data is organized in rows representing player names and columns representing statistical features. To enable mathematical analysis, this data is then transformed into a matrix form, where each row corresponds to a player and each column corresponds to a specific statistic.

Fig. 3.1. Matrix Representation of the Data

The data matrix is then transposed so that each row represents a statistical feature, while each column represents a player.

After transforming the NBA player statistics into matrix form, the next step in data preparation is data normalization. Normalization is applied because each statistical feature has a different scale and range of values. For example, points per game usually have larger numerical values compared to rebounds or field goal percentage. If the data is used directly without normalization, statistics with larger values may dominate the analysis results.

In this study, normalization is performed using the standardization (Z-score) method, where each statistical value is adjusted based on its mean and standard deviation. This process ensures that each column in the data matrix has a mean value of zero and a standard deviation of one. By applying normalization, all statistical features are placed on the same scale, allowing Singular Value Decomposition (SVD) to analyze player performance more fairly and accurately.

3.2. Singular Value Decomposition

After the data has been preprocessed, normalized, and transposed—so that each column represents a player and each row represents a statistical feature—it is ready for Singular Value Decomposition (SVD) analysis. SVD is a mathematical technique used to decompose a matrix into three separate matrices: U, S, and Vt. This decomposition allows us to identify underlying patterns in the data, reduce dimensionality, and understand how different statistics and players contribute to overall performance. By applying SVD to the NBA player statistics, we can systematically analyze the relationships between different performance metrics and highlight the dominant factors that characterize player value.

Fig. 3.2. Matrix U

Matrix U represents the combination of statistical features across different dimensions. Each column in U corresponds to a specific latent pattern of statistics that exist in the dataset. For example, one column might capture offensive contributions such as points and assists, while another might capture defensive contributions like steals and blocks. This matrix is particularly useful when the data contains statistics with different scales, as it allows us to identify patterns that are independent of the original units. In this study, matrix U helps to understand how different NBA statistics combine to form meaningful performance dimensions for the 2025–2026 season.

Fig. 3.3. Matrix Vt

Matrix Vt represents the contribution of each player to the latent statistical patterns identified in U. Each row of Vt corresponds to a latent pattern, and each column corresponds to a player. By analyzing Vt, we can determine which players strongly contribute to specific performance patterns, which is essential for ranking and identifying potential MVP candidates. In this study, Vt is used to analyze the 2025–2026 NBA season and select the top 10 players whose contributions align most strongly with the dominant performance patterns.

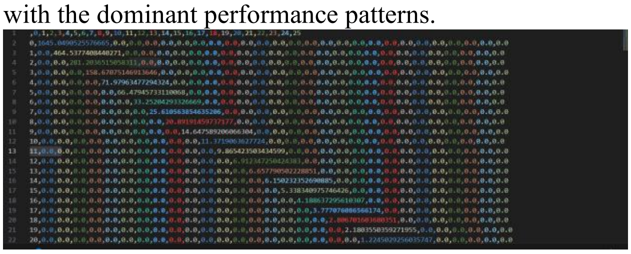


Fig. 3.4. Matrix S

Matrix S is a diagonal matrix that contains the singular values associated with each latent pattern. These values represent the importance or weight of each pattern in explaining the overall variance in the data. Larger singular values indicate that the corresponding pattern captures more of the data's structure. Matrix S can be used in further analysis to weight the contribution of different statistical patterns, providing a more nuanced understanding of player performance. By combining the information from U, S, and Vt, this study creates a robust framework for objectively identifying and ranking NBA MVP candidates based on their overall statistical impact.

3.3. Ranking MVP candidates

After performing Singular Value Decomposition (SVD) on the normalized and transposed NBA player statistics matrix, the next step is to rank potential Most Valuable Player (MVP) candidates. The decomposition produces three matrices—U, S, and Vt—that together capture the structure of the data. Matrix Vt, in particular, shows how much each player contributes to the latent statistical patterns identified in U, while matrix S provides the weighting of each pattern. By combining this information, it is possible to calculate a score for each player that reflects their overall impact across multiple performance dimensions.

The ranking process begins by considering the contribution of each player to the dominant patterns, which are the patterns associated with the largest singular values in matrix S. These patterns represent the most significant combinations of statistics in the dataset, meaning that players who score highly in these patterns are contributing strongly to the overall performance metrics. By summing the weighted contributions across these dominant patterns, a composite score is generated for each player.

Once all players have a composite score, they can be ranked from highest to lowest. The players with the top scores are identified as the strongest candidates for the MVP award. This method ensures that the ranking is objective, as it relies entirely on statistical contributions rather than subjective opinions or narratives. Additionally, using SVD allows the analysis to capture relationships between statistics that might not be obvious when looking at individual metrics, providing a more holistic view of player performance.

Finally, the top 10 players based on this ranking are highlighted as MVP candidates for the 2025–2026 NBA season. These candidates represent players who consistently contribute across multiple key statistical patterns, demonstrating both offensive and defensive impact. By using this SVD-based approach, the study provides a systematic, data-driven framework for evaluating player value and identifying potential MVPs in a fair and mathematically rigorous manner.

3.4. Experiment with 2025–2026 NBA Data

To test the proposed SVD-based methodology, an experiment is conducted using NBA player statistics from the 2024–2025 season. The purpose of this experiment is to demonstrate how historical data can be used to identify patterns in player performance and to prepare the matrix U for subsequent analysis of MVP candidates in the 2025–2026 season.

The first step is data collection, where statistics for all players from the 2024–2025 NBA season are gathered, including points per game (PTS), rebounds (REB), assists (AST), steals (STL), blocks (BLK), field goal percentage (FG%), and turnovers (TOV). The data is then organized into a matrix, where each row represents a player and each column represents a specific statistic.

Next, the data is normalized using the standardization (Z-score) method to ensure that each statistical feature contributes equally to the analysis. After normalization, the matrix is transposed so that rows represent statistical features and columns represent players. This prepared matrix is then decomposed using Singular Value Decomposition (SVD) to produce the matrices U, S, and Vt.

For this experiment, matrix U is particularly important, as it represents the combination of statistical features across latent performance dimensions. This matrix captures the dominant patterns of player statistics from the 2024–2025 season. These patterns are then used as a reference to analyze the 2025–2026 NBA data, allowing the identification of potential MVP candidates based on how closely their current season performance aligns with the established patterns in U.

Finally, by combining the historical matrix U with current 2025–2026 player statistics, the top 10 players are identified as the strongest MVP candidates. This approach demonstrates the practical use of SVD for both historical analysis and predictive evaluation, providing a systematic, data-driven framework for assessing player performance and ranking potential MVPs.

IV. Result And Discussion

4.1. Result

Using the methodology described previously, the NBA player statistics were analyzed to identify the top MVP candidates. The results of the analysis are presented in Table I, which shows the top 10 players based on their composite scores calculated using the SVD approach.

TABLE I. Test Results (2024–2025 Data)

Player Name	Score
Nikola Jokić	0.133945
Giannis Antetokounmpo	0.132454
Shai Gilgeous-Alexander	0.120930
Luka Dončić	0.115379
Cade Cunningham	0.108036
Karl-Anthony Towns	0.105732
Anthony Davis	0.105227
Jayson Tatum	0.105129
Victor Wembanyama	0.104219
James Harden	0.100593

From this table, it can be seen that Nikola Jokić emerges as the strongest MVP candidate based purely on statistical analysis.

When compared to the real-life MVP results for the 2024–2025 season (Table II), some differences are observed.

TABLE II. Real Life Result MVP 2024-2025

Player Name
Shai Gilgeous-Alexander
Nikola Jokić
Giannis Antetokounmpo
Jayson Tatum
Lebron James
Cade Cunningham
Anthony Edwards
Stephen Curry
Jalen Brunson
James Harden
Evan Mobley

Although the SVD-based ranking differs from the actual MVP results, Shai Gilgeous-Alexander, the official MVP, is still ranked third in the test results. This indicates that his statistics during the season were strong and justify him as a highly qualified MVP candidate.

Given that the test results align reasonably well with real-world outcomes, it is concluded that the methodology is effective. Therefore, matrix U from the SVD of 2024–2025 data can be used as a reference to identify the strongest MVP candidates for the ongoing 2025–2026 season.

The results of this experiment for the 2025–2026 data are presented in the table below:

TABLE I. TEST RESULTS

Player Name	Score
Nikola Jokić	1.000000
Shai Gilgeous-Alexander	0.947796
Jaylen Brown	0.918897
Deni Avdija	0.914234
Tyrese Maxey	0.914234
Donovan Mitchell	0.902563
Anthony Davis	0.898639
Cade Cunningham	0.877847
Jalen Johnson	0.866017
Brandon Ingram	0.861197
Pascal Siakam	0.852542

From this experiment, it can be observed that, based purely on statistics, Nikola Jokić again appears as the strongest MVP candidate for the 2025–2026 season. Interestingly, he was previously ranked second in the 2024–2025 season. This demonstrates the consistency and predictive potential of the SVD-based methodology in identifying top-performing players, even when applied to new seasons.

4.2. Discussion

From the results, it is clear that Singular Value Decomposition (SVD) can be used as a tool to identify the strongest MVP candidates in the NBA. The methodology demonstrates that players who perform well statistically are effectively highlighted, and many of the top-ranked players in the SVD results correspond to the top performers in real life.

The use of SVD for MVP candidate selection can be considered reasonably accurate because players who rank highly in reality often remain within the Top 10 in the SVD-based rankings. This shows that statistical analysis captures a large portion of player performance patterns and can provide a solid reference for evaluating potential MVPs.

However, it is important to note the limitations of using SVD alone. The MVP ranking based purely on SVD reflects only statistical performance on paper. In reality, MVP selection involves additional factors, including team contribution, fan and media voting, the number of games played in a season, leadership, and other qualitative aspects that are not recorded in the statistics. Therefore, while SVD is a valuable tool for analyzing performance and identifying strong statistical candidates, it cannot fully replace the official MVP selection process, which takes multiple human and contextual factors into account.

V. CONCLUSION

There are many approaches that can be used to determine strong MVP candidates in the NBA. Among these, the Singular Value Decomposition (SVD) approach demonstrates satisfying results when using only written statistical data. By analyzing player performance metrics through SVD, it is possible to identify the top players who have the strongest statistical contributions.

Although this approach does not consider external factors such as team contribution, fan and media voting, or other qualitative aspects, the SVD method still provides results that are reasonably consistent with real-world outcomes. Many players identified as top candidates in the SVD analysis also appear in the actual MVP rankings, showing that statistical analysis alone can capture much of the performance patterns that determine player value.

Therefore, SVD can be considered a useful and effective tool for analyzing NBA player statistics and highlighting potential MVP candidates. While it may not replace the official MVP selection process, it serves as a strong data-driven reference for understanding player performance and evaluating statistical contributions in a fair and systematic way.

VI. APPENDIX

To complement this research paper, several external resources are provided for readers to explore the implementation and processes involved in this study:

1. Source Code Repository

All source code used in this study is publicly available on the following GitHub repository:

https://github.com/Jerannn24/nba-mvp-candidates-svd.git

2. Research Presentation Video

A brief explanation of the background, methodology, and results of this research is also presented in a video format, which can be accessed via the following link:

https://youtu.be/_Z5rMaTegis

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PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

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