

Evaluating First-Round NBA Draft Picks: Bust or Success? DSC 405 (001) Web Scraping Project

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Project Objective & Problem Statement

- Every year, athletes join the NBA Draft, with a handful making it to the first round, which often leads to better salaries and recognition. These players are anticipated to perform exceptionally, but a significant number end up not meeting expectations.
- **Problem Statement:** This project seeks to quantify the success rate of NBA first-round draft picks by comparing their individual performance statistics to the league averages.
- **Problem Metrics:** Success is defined as stats equal to or greater than the average, while lower stats indicate a bust.

Data Source and Variables

- **Website:** Basketball Reference
- **Url:**
https://www.basketball-reference.com/leagues/NBA_2024_totals.html
- **Limitations:** N/A
- **Explanatory Variable:** Statistics of the first-round picks, which include Points per Game, Rebounds per Game, Assists per Game, Steals per Game, and Turnovers per Game.
- **Response Variable:** Status of the first-round picks, which is determined based on whether their statistics are greater than equal to, or lower than the league's first-round draft picks averages. This status is categorized as either 'successful' or 'bust'.
- **Information Status:** HTML



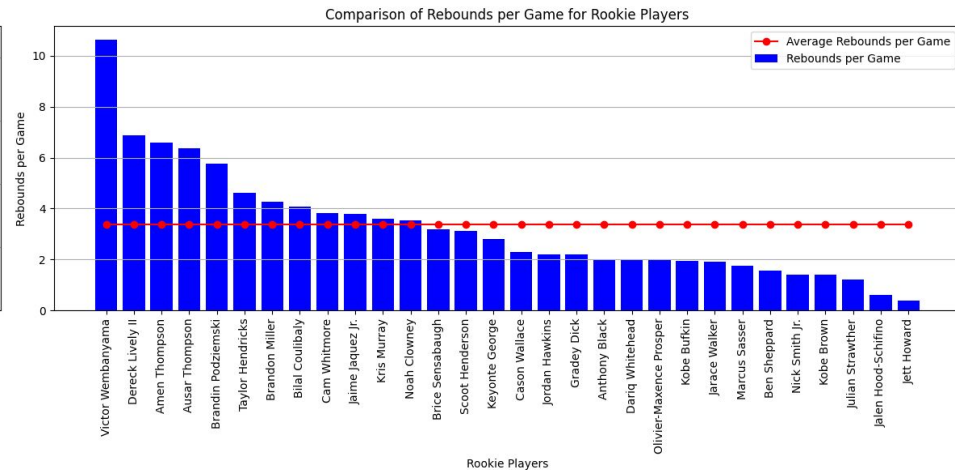
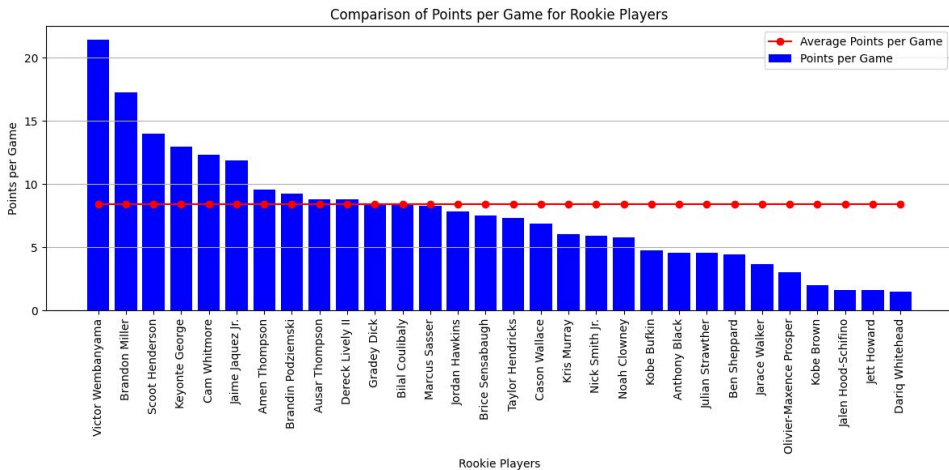
Data Moves

1. Import necessary libraries and load the website's HTML data. This is the initial setup where you bring in the tools you need and the data you'll be working with.
2. Transform the HTML data into a usable data frame. This involves finding the appropriate HTML tags and classes that contain the data you're interested in, and converting that data into a structured format.
3. Select the columns needed for analysis. The columns "Player", "G", "PTS", "TRB", "AST", "STL", and "TOV".
4. Combine rows with the same player names. This step consolidates data for each player if they appear in multiple rows.
5. Calculate per-game statistics. Using the columns "PTS", "TRB", "AST", "STL", and "TOV", create new columns 'Points per Game', 'Rebounds per Game', 'Assists per Game', 'Steals per Game', 'Turnovers per Game' by dividing the values into these columns by the number of games played ('G' column).
6. Calculate average statistics. Create new columns 'Average Points per Game', 'Average Rebounds per Game', 'Average Assists per Game', 'Average Steals per Game', and 'Average Turnovers per Game' by finding the means of the 'Points per Game', 'Rebounds per Game', 'Assists per Game', 'Steals per Game', 'Turnovers per Game' columns.
7. Visualize the data. Create bar charts comparing the rookie players and their 'Points per Game', 'Rebounds per Game', 'Assists per Game', 'Steals per Game', and 'Turnovers per Game'.
8. Calculate and visualize differences. Calculate the difference between the players' per-game statistics and the average statistics, and plot these differences on a bar chart. This will give you a visual representation of how each player compares to the average.

Final DataFrame for Analysis/Visualization

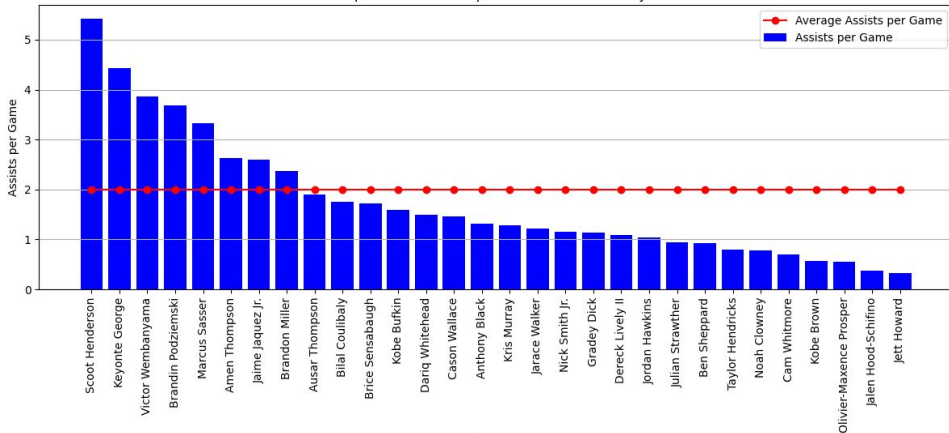
	A	B	C	D	E	F	G	H	I	J	K	L
1	Player	G	Points per Game	Rebounds per Game	Assists per Game	Steals per Game	Turnovers per Game	Average Points per Game	Average Rebounds per Game	Average Assists per Game	Average Steals per Game	Average Turnovers per Game
2	Amen Thompson	62	9.548387096774194	6.596774193548387	2.629032258064516	1.2580645161290323	1.4516129032258065	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
3	Anthony Black	69	4.579710144927536	2.0144927536231885	1.318840579710145	0.5072463768115942	0.8115942028985508	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
4	Ausar Thompson	63	8.825396825396826	6.380952380952381	1.9047619047619047	1.0793650793650793	1.3333333333333333	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
5	Ben Sheppard	57	4.421052631578948	1.5614035087719298	0.9298245614035088	0.2631578947368421	0.2631578947368421	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
6	Bilal Coulibaly	63	8.444444444444445	4.063492063492063	1.746031746031746	0.9047619047619048	1.380952380952381	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
7	Brandin Podziemski	74	9.216216216216216	5.77027027	3.689189189189189	0.8243243243243243	1.1891891891891893	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
8	Brandon Miller	74	17.283783783783782	4.256756756756757	2.364864864864865	0.8918918918918919	1.7837837837837838	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
9	Brice Sensabaugh	32	7.53125	3.1875	1.71875	0.40625	1.46875	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
10	Cam Whitmore	47	12.319148936170214	3.8297872340425534	0.7021276595744681	0.6382978723404256	0.9787234042553191	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
11	Cason Wallace	82	6.841463414634147	2.2804878048780486	1.4634146341463414	0.926829268	0.5487804878048781	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
12	Dariq Whitehead	2	1.5	2	1.5	0	0	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
13	Dereck Lively II	55	8.781818181818181	6.872727272727273	1.0909090909090908	0.6545454545454545	0.9090909090909091	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
14	Grady Dick	60	8.5	2.2	1.1333333333333333	0.5666666666666667	0.8333333333333334	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
15	Jaime Jaquez Jr.	75	11.853333333333333	3.8	2.6	1.0266666666666666	1.4666666666666666	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
16	Jalen Hood-Schifino	21	6.190476190476191	0.6190476190476191	0.38095238095238093	0.14285714285714285	0.42857142857142855	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
17	Jarace Walker	33	6.363636363636362	1.9090909090909092	1.2121212121212122	0.45454545454545453	0.5151515151515151	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
18	Jett Howard	18	1.6111111111111112	0.3888888888888889	0.3333333333333333	0.1111111111111111	0.16666666666666666	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
19	Jordan Hawkins	67	7.820895522	2.208955223880597	1.044776119402985	0.2835820895522388	0.5970149253731343	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
20	Julian Strawther	50	4.54	1.22	0.94	0.34	0.46	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
21	Keyonte George	75	12.986666666666666	2.8133333333333335	4.426666666666667	0.48	2.5066666666666667	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
22	Kobe Brown	44	2.022727272727273	1.4090909090909092	0.5681818181818182	0.2727272727272727	0.20454545454545456	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
23	Kobe Bufkin	17	4.764705882352941	1.9411764705882353	1.588235294117647	0.4117647058823529	0.5882352941176471	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
24	Kris Murray	62	6.064516129032258	3.6129032258064515	1.2903225806451613	0.8548387096774194	0.8870967741935484	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
25	Marcus Sasser	71	8.253521126760564	1.7605633802816902	3.323943661971831	0.6197183098591549	1.267605633802817	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
26	Nick Smith Jr.	51	5.921568627450981	1.411764705882353	1.1568627450980393	0.19607843137254902	0.7647058823529411	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
27	Noah Clowney	23	5.782608695652174	3.5217391304347827	0.782608696	0.34782608695652173	0.6521739130434783	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
28	Oliver-Maxence Prosperi	40	3.025	1.975	0.55	0.175	0.2	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
29	Scot Henderson	62	14.129032258064516	5.419354838709677	0.7741935483870968	3.4193548387096775	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372	
30	Taylor Hendricks	40	7.3	4.625	0.8	0.7	0.675	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372
31	Victor Wembanyama	71	21.43661971830986	10.633802816901408	3.859154929577465	1.2394366197183098	3.6619718309859155	8.422299784791328	3.3747019906679503	2.0012952406136204	0.590349783	0.9815656102519372

Findings/Visualizations



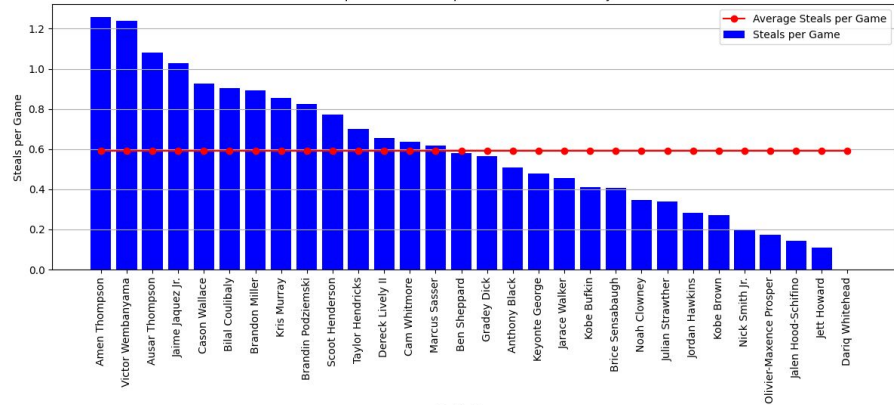
Comparison of Points & Rebounds Per Game for Rookie Players

Comparison of Assists per Game for Rookie Players



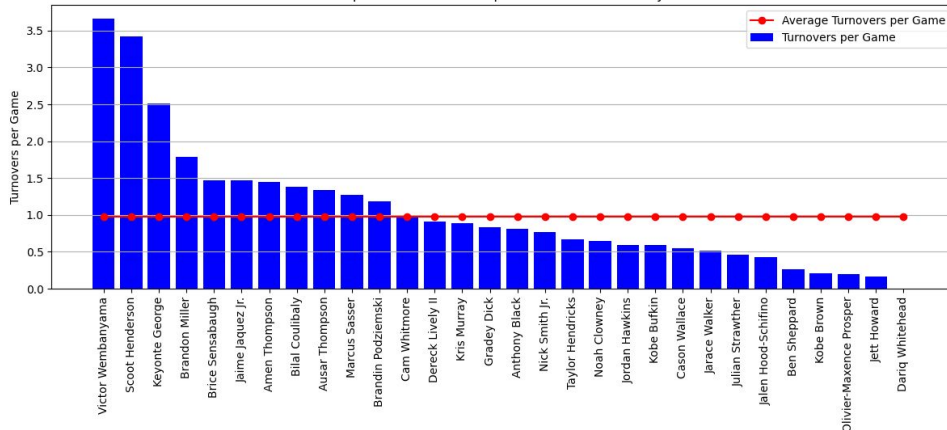
Rookie Players

Comparison of Steals per Game for Rookie Players



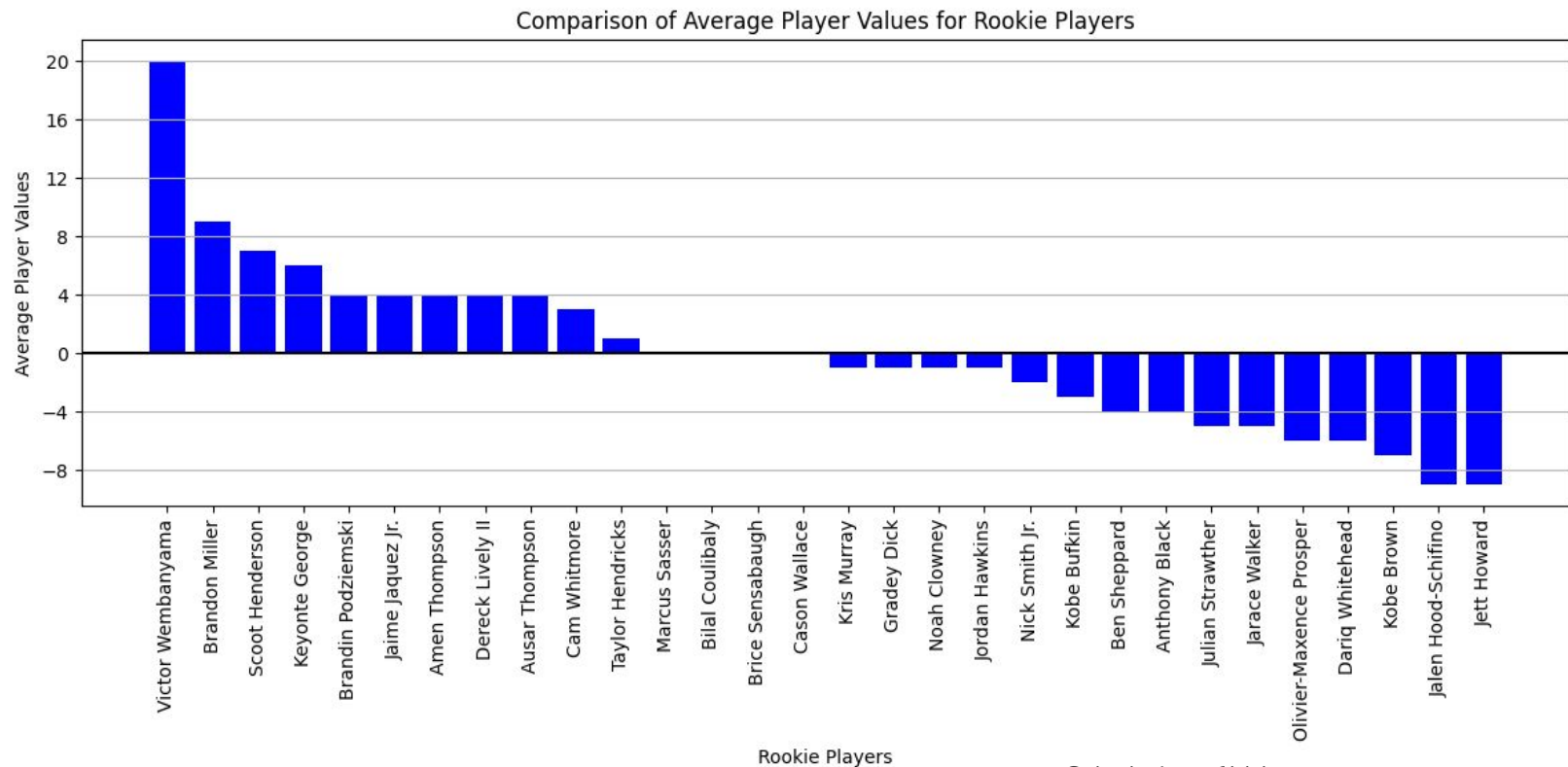
Rookie Players

Comparison of Turnovers per Game for Rookie Players



Rookie Players

Comparison of Assists, Steals, & Turnovers per Game for Rookie Players



Comparison of Average Player Values for Rookie Players

Calculation of Value

- Add: Difference of Individual Player Points, Assists, Steals, & Rebounds from League Average
- Subtract: Difference of Individual Player Turnovers from League Average



Findings

Success (all playing at a level equal or above the league average according to our parameters): Victor Wembayama, Brandon Miller, Scoot Henderson, Keyonte George, Brandin Podziemski, Jamie Jaquez Jr., Amen Thompson, Dereck Lively II, Ausar Thompson, Taylor Hendricks, Marcus Sasser, Billy Coulibaly, and Brice Sensabaugh.

Bust (all playing at a level below the league average according to our parameters): Cason Wallace, Kris Murray, Gradey Dick, Noah Clowney, Nick Smith Jr., Kobe Bufkin, Ben Sheppard, Anthony Black, Julian Strawther, Jarace Walker, Oliver-Maxence Prosper, Dariq Whitehead, Kobe Brown, Jalen Hood-Schifino, and Jett Howard



Use Case of Research and Future Projects

Use Case of Research:

- **NBA Fans:** They can gain insights about the potential performance of their favorite team's rookies.
- **Sports Analysts:** They can use the data for in-depth analysis and predictions.
- **NBA Teams:** They can use the insights for strategic decision-making during drafts.
- **Fantasy League Players:** They can make informed decisions when picking players for their fantasy teams.
- **Sports Journalists:** They can use the data for articles and reports on player performance.
- **Sports Bettors:** They can use the information to make informed bets.

Future Projects:

- **Player Performance Prediction:** This project could use machine learning algorithms to predict future performance of players based on their current stats.
- **Team Strategy Analysis:** This project could analyze the data to help teams develop strategies for game play, player selection, and training.
- **Fantasy League Optimization:** This project could help fantasy league players to optimize their team selection based on player stats. It could also predict the performance of players in upcoming games.