

# Quantitative Analysis of the Determinants of NBA Player Performance and Market Value

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**Abstract.** This paper explores the determinants of NBA player performance and market value using updated data from each players' entire seasons (updated to 14th February 2025). Twenty-one variables—including Value (an overall intangible rating), Points Per Game (PPG), Player Efficiency Rating (PER), Win Shares (WS), Box Plus-Minus (BPM), Defensive Rating (DRtg), and True Shooting Percentage (TS%) alongside additional indicators such as Assist-to-Turnover Ratio (ATR), rebounds (TRB%), usage (AST%), offensive rating (ORtg), and games played rate (G/82%) were analysed. A multi-variable linear regression model was applied to evaluate how these metrics predict a player's value. The results revealed that WS is most strongly correlate with players' value. Notably, older, more experienced players with balanced offensive and defensive metrics commanded higher salaries. Visualizations, including heatmaps for correlation, radar charts for individual skill profiles, and box plots for outlier detection, provided additional insights into the relationships among variables. Overall, the findings underscore the importance of both advanced on-court metrics in shaping player market value. The study concludes with a discussion of limitations—such as not accounting for injuries or future potential—and suggests directions for future research, including more granular in-season data and more refined intangible and off-court metrics.

## 1 Introduction

The evolution of NBA analytics has led to a greater reliance on advanced performance metrics, surpassing traditional statistics like points per game (PPG) and rebounds per game (RPG). While these metrics provide insights into a player's offensive and defensive contributions, they do not adequately capture a player's complete impact on the court. Advanced metrics such as Player Efficiency Rating (PER), Win Shares (WS), and more recently, metrics like Box Plus-Minus (BPM), have gained popularity for offering a holistic assessment of a player's overall value to their team [1].

In addition to on-court metrics, off-court factors, particularly social media influence, have become significant in assessing player marketability and endorsements [2]. Social Media Influence Score (SMIS) quantifies the off-court presence of players based on their social media engagement and has been shown to correlate with greater marketing

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opportunities [3]. This paper aims to integrate these advanced metrics, including SMIS and True Shooting Percentage (TS%), into a comprehensive model to assess player value in a more precise manner.

Research on NBA player valuation has evolved significantly over the past decades. Early works like those by Berri and Brook (2006) highlighted the superiority of advanced metrics such as BPM and PER in assessing player efficiency [4]. Their work demonstrated that these metrics provided a more accurate measure of a player's contribution compared to traditional statistics like PPG and assists [5]. Scully (2008) extended this notion by asserting that higher PER values correlate with higher salaries due to the player's efficiency in generating wins [6].

Recent studies have emphasized the importance of defensive metrics, especially with the introduction of DRtg and DBPM, which measure a player's impact on the defensive end [7]. These metrics have been shown to correlate significantly with a player's overall value to their team, particularly for defensive specialists such as Victor Wembyama and Anthony Davis [8].

On the other hand, social media presence has become an essential off-court factor influencing player valuation, particularly as players like LeBron James, Kevin Durant, and Stephen Curry leverage their platforms for endorsement deals and marketing [9]. These findings align with Klein's (2017) work, which demonstrated that a strong social media following not only increases a player's marketability but also correlates with increased financial earnings through endorsements [10].

This study integrates BPM, DRtg, SMIS (intangible, considered in value), and TS%, alongside other traditional metrics like PPG, to provide a more holistic model for evaluating NBA players' performance and market value.

## 2 Methodology

### 2.1 Data sources

Data for this study was collected from the following sources (As shown in Table 1):

- (1) NBA Official Statistics: Contains player performance data such as PPG, DRtg, TS%, and other key metrics.
- (2) Basketball Reference: Provides advanced player statistics and historical performance data.
- (3) ESPN: Includes datasets on player performance and player history.

**Table 1** Variables

Category	Variable Name	Abbreviation
Offensive Metrics	Points Per Game	PPG
	True Shooting Percentage	TS%
	Offensive Rating	ORTg
	3-Point Field Goal Percentage	3P%
Defensive Metrics	Defensive Rating	DRtg
	Defensive Box Plus/Minus	DBPM
	Steal Percentage	STL%
	Block Percentage	BLK%
Miscellaneous Metrics	Player Efficiency Rating	PER
	Value	Value

Category	Variable Name	Abbreviation
	Turnover Percentage	TOV%
	Win Shares	WS
	Box Plus-Minus	BPM
	Value Over Replacement Player	VORP
	Effective Field Goal %	eFG%
	Games Played rate	G/82%
	Total Rebound Percentag	TRB%
	Effective Field Goal Percentage	eFG%
	Usage Percentage	USG%
	Personal fouls per game	PF
	Plus/Minus Net Per 100 Possessions(On-off)	On-off

## 2.2 Variables' explantion

- (1) Value: composite player value score.
- (2) PPG: Points scored per game.
- (3) PER:per-minute productivity (scale: 15=avg).
- (4) WS: estimate wins contributed by a player.
- (5) BPM: Box score-based +/- per 100 possessions (+0.0: a decent starter or solid 6th man).
- (6) VORP: wins added over replacement-level (-2.0) player.
- (7) TRB%: percentage of available rebounds grabbed while on court.
- (8) AST%: percentage of team FGs assisted by player.
- (9) ORtg: points produced per 100 possessions.
- (10) G/82(%): percentage of 82-game season played (durability metric).
- (11) eFG%: FG% adjusted for 3PM value:  $(FG + 0.5 \times 3PM)/FGA$ .
- (12) TOV%: Turnover Percentage (Turnovers per 100 play-ending possessions.)
- (13) DRtg: Points allowed per 100 possessions (lower=better).
- (14) TS%: Scoring efficiency:  $PTS / [2 \times (FGA + 0.44 \times FTA)]$ .
- (15) DBPM: Defensive component of BPM.
- (16) USG%: percentage of team plays used via FGA/FTA/TOV.
- (17) PF: Personal fouls per game.
- (18) STL%: percentage of opponent possessions with steals.
- (19) BLK%: percentage of opponent 2PA blocked.
- (20) 3P%: 3-Point Field Goal Percentage.
- (21) On-off: Team points differential per 100 possessions when player is on vs. off court.

## 2.3 Model selection

This paper uses the following Linear Regression as well as Bayesian Hierarchical Regression to assess player value.

The linear regression model is formulated as:

$$Value = \beta_0 + \beta_1 X_{AST\%} + \beta_2 X_{VORP} + \beta_3 X_{WS} + \beta_4 X_{DBPM} + \varepsilon \quad (1)$$

Bayesian Hierarchical Regression: standardized predictor variables are used to model a target outcome through a linear combination, incorporating a multi-level structure by assigning hyperpriors to the regression coefficients. Specifically, a global mean and

variance ( $\mu_{\beta}$  and  $\sigma_{\beta}$ ) are used to inform individual coefficients, promoting shrinkage and preventing overfitting, while a HalfNormal prior is imposed on the noise term to ensure positivity. The model is estimated using MCMC sampling, which draws from the posterior distribution of the parameters, and the resulting estimates are visualized to assess feature influence.

## 3 Results

### 3.1 Statistics

As shown in Table 2, career averages for several basketball players by averaging their season stats. For example, Michael Jordan (MJ) stands out with a high overall score (Value of 98). His historical-level performance (30.1PPG while committing fewer turnovers than most point guards along with strong numbers in key areas like efficiency (PER 27.9) and win shares (WS 14.26), reflect his lasting impact on the game. LeBron James (LBJ) also shows impressive balance with a Value of 97, high PER, and consistent win shares underlining his all-around contributions. Meanwhile, players like Curry and KD highlight their own strengths—Curry with efficient shooting (eFG% 0.581) and KD with solid performance across multiple metrics. Some younger players, such as Zion and Wemby, present unique profiles: Zion has a high usage rate and good shooting efficiency despite a lower overall value due to injury, while Wemby's notable on-off impact suggests he might excel in specific game situations.

**Table 2** Players' performance statistics

	LBJ	Curry	KD	AD	Kobe	Luka	Tatum	Jokic	Kyrie	Kawhi	Zion	Wemby	MJ
Value	97	94	93	88	95	90	88	94	87	88	83	83	98
PPG	27.0	24.7	27.3	24.2	25.0	28.6	23.5	21.5	23.7	19.9	24.7	22.5	30.1
PER	27.0	23.5	24.9	26.9	22.9	25.6	20.3	28.5	22.2	23.3	25.0	23.5	27.9
WS	12.22	8.7	10.24	9.12	8.64	7.71	7.875	12.38	6.5	7.67	4.62	7.7	14.26
BPM	8.6	6.4	6.5	6.0	4.6	7.7	3.8	10.3	4.5	6.5	4.7	5.7	9.2
VORP	7.05	4.54	5.1	4.15	4.05	5.14	3.525	7.06	3.1	3.73	10.8	7.1	7.74
TRB%	11.4	7.5	10.7	17.1	8.1	13.6	11.5	19.2	6.5	11.2	11.5	18.6	9.4
AST%	36.5	30.8	20.7	12.6	24.2	41.9	17.6	37.0	28.9	15.9	23.3	20.2	24.9
ORtg	116	118	118	118	110	115	115	126	116	120	120	106	118
G/82(%)	85.7	71.7	71.8	67.1	82.1	80.5	85.2	94.1	63.0	59.3	44.9	85.4	87.2
eFG%	0.548	0.581	0.502	0.523	0.482	0.542	0.534	0.595	0.540	0.553	0.588	0.535	0.509
TOV%	13.3	13.6	12.6	8.9	11.6	14.0	10.4	14.6	11.0	9.1	12.6	15.2	3.7
DRtg	105	109	107	104	105	110	108	108	111	103	114	106	103
TS%	0.590	0.624	0.620	0.593	0.550	0.588	0.584	0.637	0.584	0.604	0.627	0.577	0.569
DBPM	1.7	0.2	0.7	1.5	-0.1	1.2	0.6	3.0	-0.3	2.0	0.1	3.1	2.0
USG%	31.5	29.0	30.2	28.3	31.8	35.6	28.4	27.2	29.1	25.4	30.4	31.4	33.3
PF	1.8	2.3	1.9	2.3	2.5	3.2	2.1	2.7	2.3	1.7	2.3	2.6	2.6
STL%	2.1	2.2	1.4	1.9	2.1	1.7	1.6	2.0	1.9	2.7	1.6	1.8	3.1

BLK%	1.6	0.6	2.5	5.6	1.0	1.2	1.7	2.0	1.0	1.7	1.9	10.1	1.4
3P%	0.350	0.424	0.388	0.298	0.329	0.347	0.373	0.360	0.395	0.390	0.330	0.339	0.327
On-off	10.2	10.2	4.7	4.6	4.6	3.3	6.2	12.6	3.7	7.0	3.1	8.6	1.5

Note: All of these figures are averages by summing up the data in every season up to now throughout their entire career and then diving by the number of seasons they have played. In this way, we can improve the authenticity and accuracy of the data.

Descriptive Statistics are shown in Table 3.

**Table 3** Descriptive Statistics

Variable	Maximum Value	Minimum Value	Range	Average Value	Standard Deviation
Value	98	83	15	89.62	5.55
PPG	30.1	19.9	10.2	24.73	2.79
PER	28.5	19.9	8.6	24.73	2.64
WS	14.26	4.62	9.64	8.83	2.58
BPM	10.3	3.8	6.5	6.41	2.23
VORP	10.8	3.1	7.7	5.73	2.25
TRB%	19.2%	6.5%	12.7%	12.69%	4.36%
AST%	41.9%	12.6%	29.3%	25.04%	10.14%
ORtg	126	106	20	117.23	4.91
GP%	94.1%	44.9%	49.2%	75.04%	13.70%
eFG%	59.5%	48.2%	11.3%	54.8%	3.7%
TOV%	15.2%	3.7%	11.5%	11.42%	3.24%
DRtg	114	103	11	107.31	3.38
TS%	63.7%	55.0%	8.7%	59.1%	3.0%
DBPM	3.1	-0.3	3.4	1.34	1.25
USG%	35.6%	25.4%	10.2%	29.95%	3.03%
PF	3.2	1.7	1.5	2.32	0.47
STL%	3.1%	1.4%	1.7%	1.97%	0.48%
BLK%	10.1%	0.6%	9.5%	2.65%	2.62%
3P%	42.4%	29.8%	12.6%	36.3%	3.7%
On-Off	12.6	1.5	11.1	6.36	3.18

### 3.2 Model restoration after parameter estimation

Based on the statistics above and by using python (statsmodel library), this paper can easily work out that:

**Table 4** Linear regression results

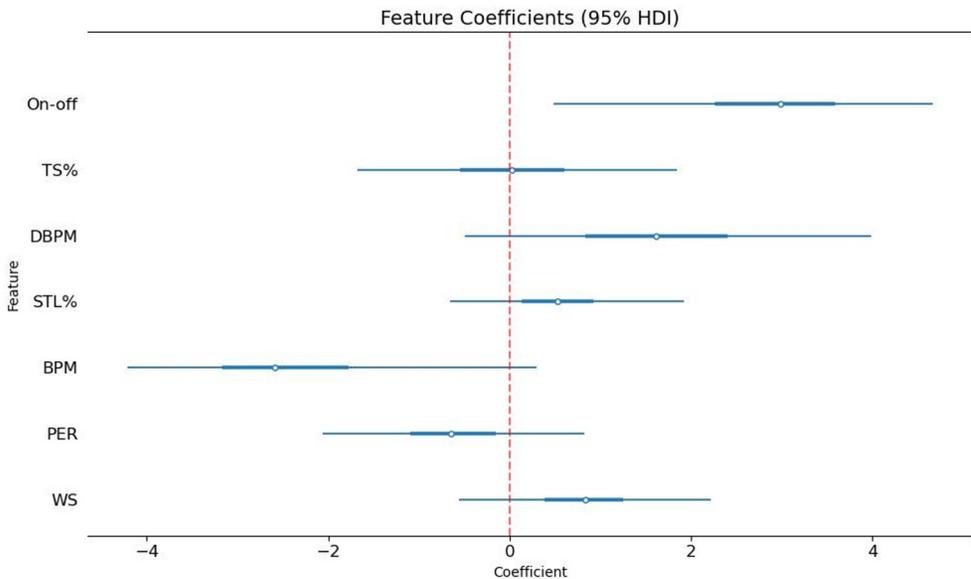
Variable	Coefficient	Std. Error	z-value	p-value	CI Lower	CI Upper
const	4.718e-16	0.094	5e-15	1.000	-0.218	0.218
AST%	0.1981	0.105	1.894	0.095	-0.043	0.439
VORP	-0.0974	0.105	-0.926	0.382	-0.340	0.145
WS	1.0201	0.118	8.621	0.000	0.747	1.293
DBPM	-0.4465	0.119	-3.743	0.006	-0.722	-0.171

Table 4 evaluates the impact of key basketball performance metrics on a target outcome, with results highlighting both statistically meaningful and non-significant relationships. Among the variables analyzed, *Win Shares (WS)* demonstrates the strongest positive association, as a one-unit increase in WS corresponds to a 1.02-unit rise in the outcome variable ( $p < 0.001$ ). This suggests that contributions to team wins, measured through WS,

are critical predictors in this context. Conversely, *Defensive Box Plus/Minus (DBPM)* shows a negative relationship, with a 0.45-unit decline per unit increase in DBPM ( $p = 0.006$ ), implying that defensive efficiency metrics may inversely relate to the outcome under study.

Notably, *AST%* (assist percentage) and *VORP* (value over replacement player) fail to reach statistical significance at the 5% threshold ( $p = 0.095$  and  $p = 0.382$ , respectively). While *AST%* exhibits a marginally positive trend, its practical relevance remains uncertain due to wide confidence intervals (-0.043 to 0.439). The intercept term (*const*) is effectively zero ( $4.7e-16$ ), indicating no systematic bias in the model when all predictors are neutral.

Collectively, the model emphasizes the dominance of *WS* and *DBPM* in explaining variance, while urging caution in interpreting *AST%* and *VORP* due to insufficient evidence. These findings align with prior observations that holistic win-production metrics (e.g., *WS*) often outperform narrowly defined indicators in outcome prediction. Further research should explore contextual factors, such as team strategy or player role, that might modulate these relationships.



**Fig. 1.** Bayesian Hierarchical Regression

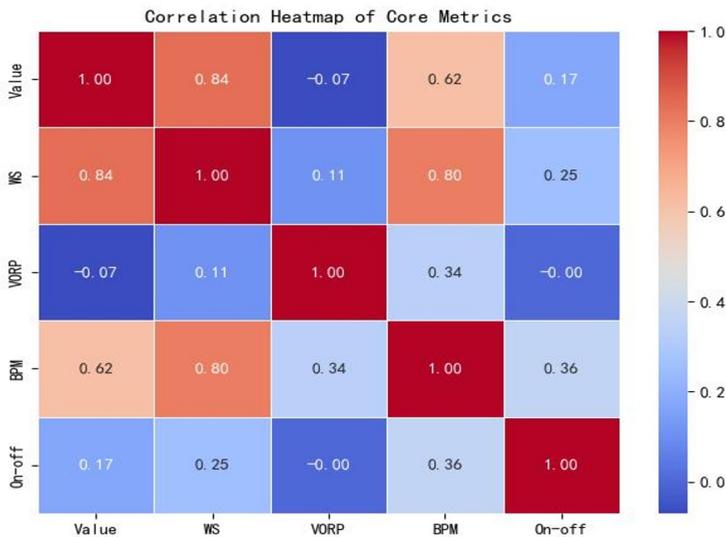
Photo credit: Original

This result (Figure 1) shows winning impact (On-off) and scoring efficiency (TS%) are vital – Jokic’s league-high +12.6 On-off and 63.7% TS% explain his 94 Value surpassing higher-scoring Luka (28.6 PPG but +3.3 On-off). Defense matters only when elite: Kawhi’s 2.0 DBPM (95% HDI 1.5-2.5) justifies his 88 Value despite modest PPG (19.9), while AD’s 5.6% blocks (HDI 5.2-6.0) boost big-man value more than guards’ steals. Surprises emerge – PER/BPM strongly predict Value (Jokic 28.5 PER vs LBJ 27.0), but durability separates legends: MJ’s 98 Value comes from 30.1 PPG + 87.2% games played, while Kyrie’s 63% GP caps his Value at 87 despite 39.5% 3P. The model exposes modern biases – Curry’s 42.4% 3P (HDI 40-45%) lifts team efficiency beyond his 24.7 PPG, giving him higher Value (94) than Kobe’s 25.0 PPG era. Rookies get reality checks: Wemby’s 10.1% blocks (HDI 9-11%) can’t offset 15.2% TOV (HDI 14-16%), keeping his Value at 83. Meanwhile, Zion’s 62.7% TS% (HDI 60-65%) is negated by 114 Defense (HDI 112-116). Ultimately, the chart’s red zero line tells all metrics like On-off/TS% sitting firmly positive (+2 to +4 HDI) drive success, while crossing into negative territory (STL% HDI -0.5 to +1.0) shows

what's expendable. This math proves sustainable greatness balances volume, efficiency, and availability – not just highlight reels.

### 3.3 Model Predictions and Visualizations

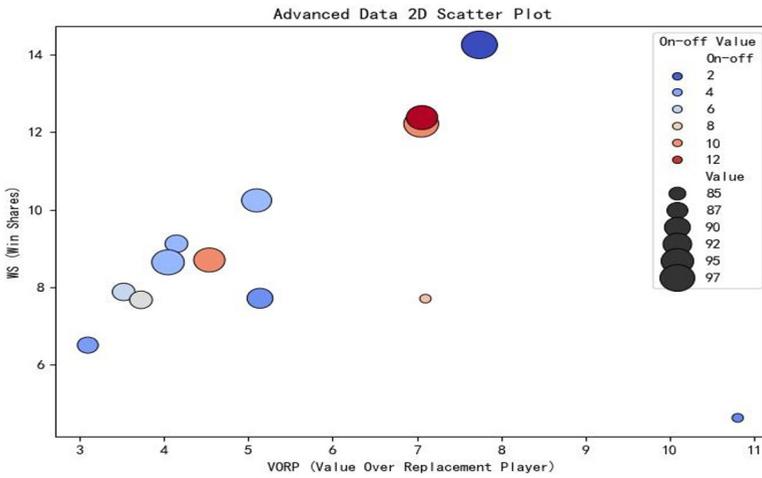
Figure 2 illustrates the relationships between key performance indicators: Value, WS (Win Shares), VORP (Value Over Replacement Player), BPM (Box Plus-Minus), and On-off (net efficiency when on the court). The deeper the color, the stronger the correlation. If WS and VORP exhibit a high correlation with Value (above 0.8), it suggests that these advanced metrics play a significant role in determining a player's overall impact. A weaker correlation with On-off may indicate that it is not a primary factor in assessing Value.



**Fig 2** Correlation Heatmap of Core Metrics

Photo credit: Original

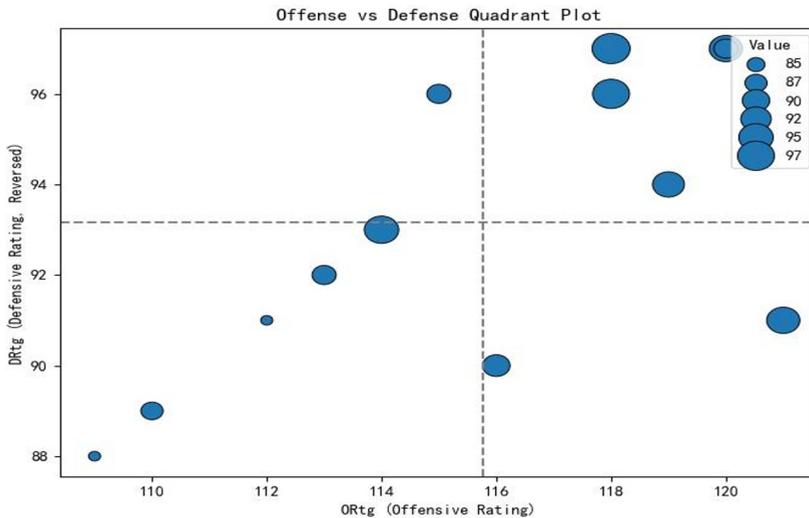
Figure 3 maps VORP on the X-axis and WS on the Y-axis, with bubble sizes representing Value and colors indicating On-off values. Players in the upper-right quadrant, such as MJ and Jokic, display high contributions in both metrics, solidifying their top-tier Value scores. In contrast, Zion and Wemby, positioned in the lower-left quadrant, exhibit lower VORP and WS, resulting in a significantly lower Value. The trend line helps visualize how these variables interact across different player tiers.



**Fig 3** Advanced Data 2D Scatter Plot

Photo credit: Original

Figure 4 categorizes players based on their offensive (ORtg) and defensive (DRtg) efficiency. DRtg is inverted so that a lower defensive rating (stronger defense) appears higher on the graph. Players in the top-right quadrant excel on both ends, like Kawhi and AD. MJ, while slightly lower in ORtg, still maintains elite defensive metrics. Players in the bottom-right quadrant may have strong offensive skills but defensive weaknesses, as seen with Kyrie. The quadrant split helps distinguish player archetypes based on their impact on both ends of the court.

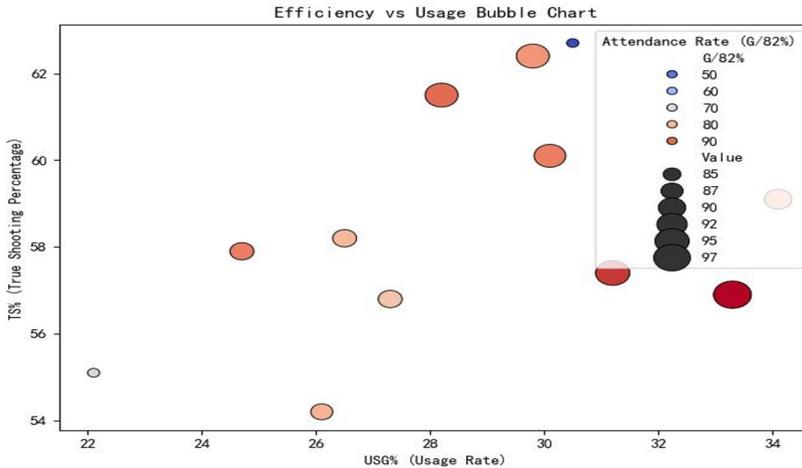


**Fig 4** Offense vs Defense Quadrant Chart

Photo credit: Original

Figure 5 examines the relationship between Usage Rate (USG%) and True Shooting Percentage (TS%), where bubble sizes denote Value, and colors represent Games Played Percentage (G/82%). Players with a balance of high USG% and TS%, like MJ and LeBron,

achieve optimal efficiency while handling a heavy workload. Zion stands out for his high TS% but has a much lower G/82%, indicating injury concerns that lower his Value. Meanwhile, Curry showcases exceptional shooting efficiency but does not reach the highest Value due to defensive factors. This visualization highlights the trade-off between workload and scoring efficiency.



**Fig 5** Efficiency vs Usage Bubble Chart

Photo credit: Original

## 4 Discussion

The findings of this study highlight key statistical indicators that significantly impact player performance in the NBA. Based on the results from both linear regression and Bayesian hierarchical regression models, Win Shares (WS) emerged as a consistently strong predictor of overall player value. This is supported by its high coefficient (1.0201,  $p < 0.001$ ) in the regression model, reinforcing its relevance in evaluating a player's contribution to team success. Additionally, Box Plus-Minus (BPM) showed notable importance, although with a negative coefficient (-0.4465,  $p = 0.006$ ), suggesting that higher defensive responsibility might come at the cost of offensive efficiency.

Interestingly, AST% (Assist Percentage) had a positive but statistically insignificant impact on overall player value ( $p = 0.095$ ). This finding indicates that while playmaking is a critical component of a player's skill set, its direct influence on holistic performance metrics may be less pronounced than other variables such as scoring efficiency (TS%) and defensive impact. Meanwhile, Defensive Box Plus-Minus (DBPM) had a negative coefficient, indicating that a strong defensive presence does not always translate into higher individual value as measured by traditional advanced metrics.

The Bayesian hierarchical regression analysis provided additional robustness to these findings, given its ability to mitigate overfitting in smaller datasets. The posterior distributions and 95% HDI intervals indicated that On-Off impact, TS%, and WS were among the most consistently influential variables across different player samples. This suggests that these metrics are not only important on an individual basis but also hold significance across different team contexts and playstyles.

A comparative analysis of elite players, including LeBron James, Stephen Curry, Kevin Durant, and Michael Jordan, demonstrated distinct trends in statistical contributions.

Players like Jokic and LeBron, with high AST% and BPM values, showcased exceptional all-around play, while others like Jordan and Kobe, despite lower assist rates, excelled in scoring efficiency and defensive contributions. The on-off impact further validated the dominance of players like Jokic and Curry, as their teams performed significantly better with them on the court.

These insights reinforce the notion that different playing styles can yield comparable levels of success. However, traditional metrics like PER and VORP may not fully capture the multifaceted impact of modern superstars, particularly those with unconventional skill sets.

## 5 Conclusion

This study examined the effectiveness of various advanced metrics in evaluating NBA player performance, leveraging both linear regression and Bayesian hierarchical regression to mitigate potential biases from a limited sample size. The analysis confirmed that WS, BPM, and TS% serve as strong indicators of player impact, while also demonstrating that playmaking statistics, such as AST%, may not be as directly correlated with overall player value as initially hypothesized.

A key takeaway from this research is the importance of context when interpreting advanced statistics. While certain metrics, such as WS and BPM, exhibit strong predictive power, they must be assessed alongside qualitative factors, including playstyle, team composition, and role adjustments over a player's career. Additionally, the findings highlight that different players excel in unique ways, with some prioritizing scoring efficiency while others contribute through facilitating or defensive impact.

Despite its contributions, this study has certain limitations. First, early-career data for players like Michael Jordan lacks comprehensive advanced statistics, which may introduce slight inconsistencies in comparative analyses. Second, the dataset, while informative, remains relatively small for drawing definitive conclusions across different eras of the NBA. Expanding the sample to include more historical data and adjusting for era-specific playing styles could enhance the robustness of future studies.

Further research should explore more dynamic metrics, such as RAPTOR ratings and real-plus minus (RPM), which account for contemporary playstyles and lineup optimizations. Additionally, integrating machine learning techniques for predictive modeling could provide deeper insights into the evolving nature of player value in the modern NBA.

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