Apples to Oranges: The Development of the Pomeroy Metric to Quantify the Value of MVP-Level Season Performances Between Positions in the NBA from 2010-2022

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Abstract

Athletic departments in small colleges and universities that seek to identify, recruit, support, and maintain high-level student-athlete talent are faced with unique and significant challenges. The ability to compete with large institutions is often not feasible and forces smaller programs to find as much value as possible in the greater athletics landscape. Sports analytics are a useful tool to understand data and statistics through new metrics. While many current metrics are designed to understand a player's value individually as well as part of their team, there are limited metrics that can be used by coaches and their staff to identify high-value players. This thesis explores key metrics at the forefront today including Wins Above Replacement (WAR), Elo Ratings, and KenPom Ratings and reviews relevant literature from the industry. The product of this research is the development of an analysis tool, The Pomeroy Metric, that evaluates players in a position-based context which allows coaches and their staff an opportunity to find value in a new and unique way. This tool is articulated using modern National Basketball Association (NBA) statistics of top-five Most Valuable Player (MVP) vote getters of the past thirteen seasons.

Keywords: analytics, metrics, WAR, NBA, college basketball, MVP

Dedication

To my wife, Olivia:
The love of my life and my best friend.

To My Parents Jeff & Julie and My Family
Who always knew I could do it and waited patiently for me to get there.

To The Woods
Who took a chance and gave me a home away from home.

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List of Terms

Analytics

"The analysis of data, typically large sets of business data, by the use of mathematics, statistics, and computer software." In the field of sports, it is the analysis of sets of data to make inferences about the performance of athletes (Dictionary.com, Analytics).

Box score

A summary of a sporting event using numbers. Box scores usually include the score of the contest, individual statistics, and other notable events that occurred including ejections and penalties. In the field of analytics, it is the primary source of information for understanding a player's performance (Merriam-Webster, box score).

Baseball-Reference Wins Above Replacement (bWAR)

A custom version of the Wins Above Replacement metric that is used by the company Baseball-Reference. It uses Runs Allowed Over 9 Innings (RA9) to calculate a baseball pitcher's score based on how many runs are allowed over the course of a 9-inning game. It differs from fWAR by placing less emphasis on the skill of a pitcher and more on the skill of the fielders (Baseball Reference, 2018).

Defensive Runs Saved (DRS)

"DRS quantifies a player's entire defensive performance by attempting to measure how many runs a defender saved. It considers errors, range, outfield arm and double-play ability. It differs only slightly from UZR (Ultimate Zone Rating) in its formula, but the concept is the same" (MLB.com, Defensive Runs Saved (DRS)).

Elo Rating

An algorithm created by (and named after) Arpad Elo (typically pronounced /iːloʊ/) , a chess player who wanted to improve on existing methods for calculating the relative skill level of players by using zero-sum game theory. The rating system began its use in chess as a way to rank players who start at a score of 1500 and see their score increase based on their wins and losses against players of different skill levels (Elo, 1966).

Field Independent Pitching (FIP)

A similar formula to Earned Run Average, FIP "focuses solely on the events a pitcher has the most control over - strikeouts, walks, hit-by-pitches, and home runs. It entirely removes results on balls hit into the field of play" (MLB.com, Fielding Independent Pitching (FIP))

FanGraphs Wins Above Replacement (fWAR)

A custom version of the Wins Above Replacement metric that is used by the company FanGraphs. It uses Fielding Independent Pitching to calculate a baseball pitcher's score based on events that they have direct control over (strikeouts, walks, and homeruns). It differs from bWAR by placing more emphasis on the skill of a pitcher (Slowinski, 2023).

KenPom Ratings

Named after their creator, Ken Pomeroy, they are a metric that is used to evaluate and predict the success of NCAA Division I college basketball teams. The ratings are listed on his website every season and are updated using a unique formula throughout the season (Pomeroy, 2023).

Meta-Analytics

The collection of multiple studies on a subject to find patterns and variances on a large set of data (Franks, 2016).

Metrics

Tools to measure an established set of data. In the field of sports, metrics are formulated tools used to evaluate or collect data for further analysis. They are the means by which data is gathered and processed. (Merriam-Webster, metric)

Most Valuable Player (MVP)

An award given to players to denote the best player in a league or at a position based on an established set of criteria depending on the governing body of the sport. At the professional level, the MVP award is considered the highest individual award that can be attained and is awarded to a player or players that earn the most votes from their respective committee. (Dictionary.com, MVP)

National Collegiate Athletic Association (NCAA)

Collegiate athletics governing body that represents, "More than 500,000 college athletes across all three divisions compete for about 1,100 member schools in all 50 states, the District of Columbia, Puerto Rico and even Canada" (Overview, 2021).

Name-Image-Likeness (NIL)

The ability for college athletes to profit off their name, image, and likeness in media. Previously, this was illegal and not allowed by the NCAA, but recent changes have resulted in the ability for college athletes to make money in this way (NCAA.org, 2021).

Principal Component Analysis (PCA)

A technique for analyzing large sets of data that contain various dimensions per data point with the goal of enhancing the dimensionality and creating visualization of the data (Jolliffe, 2016).

Robust Algorithm [using] Player Tracking [and] On/Off Ratings (RAPTOR)

"Robust Algorithm (using) Player Tracking (and) On/Off Ratings" is a FiveThirtyEight metric that uses play-by-play and player-tracking data to calculate each player's individual plus-minus measurements and wins above replacement (Silver, 2019).

Runs Allowed Over 9 Innings (RA9)

Total runs allowed over 9 innings by a pitcher. Include both earned runs (hits) and unearned runs (walks, errors) (MLB.com, Runs Allowed per Nine Innings Pitched (RA9))

Sabermetrics (SABRmetrics)

Originally stylized as SABRmetrics in reference to the Society for American Baseball Research, Bill James is credited as the first to coin the term. Sabermetrics is the beginning of metrics in baseball (Society for American Baseball Research, 2023).

Sports Information Director (SID)

A staff position at colleges and universities that is traditionally the liaison between the institution and media. The position is typically responsible for the collection of statistics during contests and the maintenance of historical information.

Statistical Diversity Index (SDI)

"a quantitative measure that reflects how many different types there are in a dataset. These indices are statistical representations of [diversity] in different aspects" (22.2: Diversity Indices, 2022). A higher diversity index is evidence of more types within a dataset.

Ultimate Zone Rating (UZR)

"UZR quantifies a player's entire defensive performance by attempting to measure how many runs a defender saved. It takes into account errors, range, outfield arm and double-play ability." For example, following a fly ball play, if data says that a player makes the catch 60% of the time, then the fielder would be awarded 0.4 points based on difficulty. If the player does not catch the ball, they would lose 0.6 points (MLB.com, Ultimate Zone Rating (UZR)

Wins Above Replacement (WAR)

"Wins Above Replacement", A statistic that values a player over a replacement-level player in terms on wins for their respective club (Slowinski, 2023).

Zero-Sum Game Theory

A game theory postulating that for certain competitive contests, there is a winner and a loser. All events that occur within that contest have a positive or negative effect on every player and their ability to win or lose. (MasterClass, 2023)

Introduction

Analytics are an answer to an infinite number of questions in sports and rapidly becoming the most valuable tool available. Still, the use of analytics should never be used as the answer to a question, but instead as an explanation of a phenomenon for which there are multiple possibilities. The rise of sports metrics to determine player value through ways that were not previously available is evidenced by the large number of metrics available today. From billion-dollar franchises to small college programs, the desire to create the best product possible is seen at every level and the need to assign meaning to a long list of statistics is more important now than ever before (Conforti, 2022).

For example, the data analysis site, FiveThirtyEight.com, uses Robust Algorithm [using] Player Tracking [and] On/Off Ratings (RAPTOR) to predict a player in the National Basketball Association's (NBA) Wins Above Replacement (WAR) trajectory as well as assigning value based on a myriad of metrics. RAPTOR ratings are geared towards the modern NBA and do not value traditional "big man" (center) statistics. It's geared toward ball handlers and players that both create and capitalize on scoring opportunities. This metric uses current data to predict a player's future performance based on similar players in the past and present. RAPTOR and WAR are great metrics to understand a player's total value and how well they're performing relative to others and relative to players throughout history (Silver, 2019).

In leagues like the NBA, the use of analytics helps front offices determine contract values, coaching staffs to determine the best lineup for a game, medical staff to understand the risk that players are placing on their bodies at any given moment, players themselves to determine their legacy, and fans to settle bar arguments over the best player in the game. Determining who deserves the league's highest award, the Most Valuable Player (MVP), is one practical application of metrics. Receiving the award results in benefits for both the player and the team as players see increased exposure, positive marks towards their legacy, and often a monetary reward. For teams, employing the best player of the season can increase revenue, fan attendance, and can lead to postseason success. The ability to not only retain but also recruit talent in free agency can be a positive result of employing top talent, which is a major concern for any front office that wishes to maintain a winning team and culture (Conforti, 2022).

For players who are still in college, close attention may be paid to the performance level of MVP players as they continue to set the bar for what it means to be the best player in the NBA. Large colleges are constantly recruiting those who they believe are the best players possible in order to win championships, graduate athletes, and develop them into players worthy of being drafted by an NBA team. For smaller programs like Saint Mary-of-the-Woods College (SMWC), there may not be enough historical data available or there is a significant difficulty in obtaining top-tier talent compared to National Collegiate Athletic Association (NCAA) Division I schools. With the introduction of Name-Image-Likeness (NIL) rules and "notice of transfer" laws in the NCAA, there is a growing dichotomy between the largest programs and the smallest (Garrett, 2023). These changes, while beneficial to student-athletes, make it increasingly difficult for mid- to small-tier schools to compete. Still, there are opportunities that are left on the table throughout the country and makes competition harder and harder.

Problem Statement

This research is based on key understandings of current metrics used in professional and collegiate sports as well as the gaps that they present and the issues that both are facing today. Small colleges face difficulties in talent acquisition due to an inequality between themselves and larger institutions and thus are unable to recruit using similar tactics. While the use of professional statistics, specifically in the NBA, will be used to aid in the development and visualization of this metric, its primary purpose is for the evaluation of player performance based on position and without regard to team factors (Bruce, 2016).

In a perfect system, all college programs would have equal opportunity to recruit student-athletes, and while it might appear that way, there is a disparity between the largest colleges and the smallest in their ability to recruit. There are levels to college athletics, divisions that allow for large schools to compete with one another and small schools to do the same. For example, institutions such as Alabama, Texas, Clemson, and Purdue all compete in the NCAA Division I and within that hierarchy, they belong to conferences such as the Southeastern Conference (SEC), Atlantic Coast Conference (ACC), and the Big Ten Conference (B1G). For a small school such as SMWC, they belong to the National Association of Intercollegiate Athletics (NAIA) and the River States Conference (RSC). There is no crossover between these conferences because of numerous differences including institution size, program size, revenue, location, and student population.

Because smaller schools are recruiting relative to their pool of talent, it’s often that local student-athletes are recruited to not only provide an opportunity to stay close to home, but to encourage local participation in the sport as well as the ease of recruitment (Weathersby, 2013). Smaller schools don’t necessarily have the budget to send personnel across the country to find players and instead rely on recruitment opportunities that are within a reasonable driving range. Immediately it can become obvious that the pool of available talent is shrinking all the time as programs must carve out their own place in their region as well as compete with similar programs near them.

A distinct lack of booster programs can also lead to challenges when it comes to supporting an athletic department (Weathersby, 2013). The desire for fans to see their alma mater competitive is a driving force behind athletic donations and while any particular year might be more exciting than the next, the ability to fundraise quickly and efficiently for large schools is evident. Small colleges may tend to have a dedicated and passionate base of parents, alums, and students who wish for their teams to perform well, but not enough revenue could be flowing to help support that goal. With the ability to take a small pool of possible student-athletes, a small pool of resources, and limited time to make decisions throughout the recruitment season, it's imperative to have the ability to use a highly specific tool to identify potential "diamonds in the rough" (Javadpour, 2022).

In a way, this is a flawed approach to college athletics. The belief that a smaller school cannot and should not compete in the greater recruitment landscape is intentionally limiting. Every college program in the country is competing against one another. Building programs based on the belief that one exists in their own recruitment bubble is a recipe for failure. Instead, the question that programs are asking from the smallest college to the largest professional team is, "How do we gain an advantage?" (Conforti, 2022).

The development of an analysis tool that centers around the evaluation of players in a highly individual context would give coaches and their staff an opportunity to find value in a new and unique way. Where other metrics evaluate players relative to one another with no regard for their position or their coach's philosophy, this research would look at how such a metric would be implemented and beneficial to college athletics but using professional NBA statistics as a story-telling device.

The difficulty in staying competitive in an athletic environment that separates the "haves" from the "have nots" invites an opportunity to re-imagine how players are evaluated (Colás, 2017). Finding the best value that other programs have overlooked gives and edge to whomever is willing to change their recruitment methods. This is balanced with retaining both institutional and coaching control over the quality and schematic fit that a player might display. Developing a unique metric that truly finds the player with the most value relative to their expected output, while also supporting team personnel in their pursuit of a particular personnel scheme, is at the core of this research.

Research Questions

This researcher will seek to answer three distinct questions:

- What are the current sports metrics used and how do they measure player performances?
- What gaps currently exist when it comes to evaluating players based on high-level performances?
- Can a new metric successfully evaluate players relative to their position to determine previously unknown value?

First, current metrics will be evaluated and compared as the baseline for the state of analytics today. Not all metrics are possible to be studied here, but the most popular and most intriguing metrics will be evaluated. Specifically, WAR, Elo rankings & zero-sum game theory, and KenPom rankings. Each of these metrics seeks to answer different questions when it comes to player or team evaluation and their use in various sports shows their effectiveness to be applied in different situations. This research will be concerned with individual player performance and not team performance.

Second, any gaps that exist within these metrics will be assessed as well as their potential to either be rectified or understood within context. Significant flaws in these metrics are unlikely, but their ability to analyze data for their intended purpose will be evaluated. If there are opportunities to improve these metrics, then those opportunities will be incorporated into a new metric. While most metrics look at player performance evenly and relative to all players, this research is concerned with understanding players performing at the highest level.

Finally, if there is evidence that significant gaps allow for the development of a new metric to evaluate players based on their position, a new metric will be created. Any new metric will be developed with the purpose of answering the previously established gaps and providing a new tool to evaluate athletes based on high-level performers and relative to their position.

Relevance and Importance of Research

Saint Mary-of-the-Woods College faces a similar issue that many other small colleges face; How to compete in a changing college athletics landscape that rewards larger programs and prevents smaller ones from seeing similar benefits. With the introduction of NIL rules from the NCAA, the disparity between the offers that large Division I college and universities can make and the ones that small colleges, like SMWC, are even more inequitable. Even more of a challenge for small colleges is the difficulty in retaining effective and winning coaches and players who will likely seek or be approached by other institutions. This research would seek to provide a partial answer to the question, “How can small college athletic departments stay competitive?”

It’s clear that the need for a small college to utilize opportunities and understand their role in the athletics landscape is not minimal, but its effectiveness is still to be appreciated. When a coach is searching for players to recruit, they may be able to narrow down their targets quickly through their own research and the advice of their staff. By attending different games and tournaments, they are already aware of their team’s needs as well as their own desire to find the best player available. It’s not often that a coach limits themselves to find only players in positions of need without regards to the possibility to acquiring a top-tier talent at a position of depth. It’s still common, however, for even seasoned coaches to rely on their own intangibles and experience of the game to have the driving effect behind their decision-making.

Without the addition of analytics to support their goals, coaches are working with a limited view and making their desire to find great players an exercise in futility (Chung, 2016). It's not possible to reduce a player's impact to a few statistics, but this research was focused on how to use the tools we have available to reimagine how we analyze players.

Measured Gaps in Current Research

This research would not only examine what current metrics measure, but also how they help to solve the unique goals of different programs. The tools and values that volleyball programs see as valuable may not necessarily be the same ones of a basketball team (Yago Colás, 2017). While this research will be primarily focused on basketball, there is sufficient research of other sports that help to illustrate the importance of highly specified metrics depending on program, situation, personnel, and position (Deshpande, 2016). Key areas remain to be fully realized including predictive analysis, real-time strategy optimization, cross-sport analysis, and analytics focused on non-traditional sports.

Predictive analysis is the key to most analytics as they seek to draw inferences from available data to predict future performance of a player (Chung, 2016). Future performance could be real-time and in a very or long span of time to predict how a player might perform over the course of their professional career (Ruiz, 2015). Coaching staffs are constantly updating and adjusting their game plan throughout a contest. The progression of a contest leads to various changes such as personnel and strategy and they look to continue momentum or build momentum. While certain psychological factors play a heavy role in decision-making, real-time strategies can utilize analytics to make immediate decisions.

Cross-sport analysis is not only a major gap, but one that is difficult to realize with current metrics. Since most metrics are developed around specific sports and then potentially adapted to others, it's hard to find one that encompasses all statistical-recording sports. Finally, there remain opportunities to evaluate non-traditional sports such as gymnastics or snowboarding. Since these sports are evaluated based on judge's and there are no key stats taken, it's hard to develop metrics to evaluate their talent from numbers alone. The rise of data tracking would lead to valuable metrics focused on movement and skill level for these sports (Franks, 2015).

Remaining Gaps to Be Addressed

Following the conclusion of this research, there are several gaps that would remain and be used as the basis for future work. The use of biometric data, integration of cognitive and psychological factors, effects on fan engagement, and health and performance monitoring are all areas that need to be considered but are restricted based on available data. Because the field of advanced spatial data is still growing, it's not yet available for mass use and would not be effective for this research (Bruce, 2016). Still, each of these gaps would provide exceptional value to better understanding player skills and value.

Biometric data would provide immediate feedback of a player's health and assist in understanding their physical health. Player performance is limited to a player's ability to remain active and the introduction of biometric data to this research would provide additional context to each position (Bruce, 2016). The feedback of a point guard compared to a center would give a better indication of the physical demands of each position and how that plays a role in their ability to stay healthy.

Health and performance monitoring follows a similar path of biometric data and would be important to help prevent injury and evaluate how a player's performance is valued towards the success of the team at large. The absence of the player from play would have an impact on success, either positive or negative, and would need to be considered. The impact that a player has on their team's success can currently be represented in the NBA as a plus-minus which indicates the points scored when they player is on the court versus off. Whether or not a player is having a direct impact or an indirect impact on their team's offense and defense, it's important to note that value as a statistic. This is especially valuable when determining hidden value in a player which is the core of this research.

The importance of psychological factors in a player's performance can't be understated but are difficult to quantify, if not impossible. Momentum and team morale are unseen factors that are understood by the best analytical minds but can't be altered through statistics and can't be quantified as an obvious contributing factor to a player's success. Finally, fan engagement is perhaps the most important concern for front offices and high-level personnel as increased revenue can only come from fan support. While fan-favorite players are encouraged to perform as often as possible, load management is important to consider. Star players are asked to perform at extremely high levels for long stretches. The wear and tear they experience on the bodies can influence their ability to remain healthy for important periods of play, such as the playoffs. Continued research should consider how a player's availability influences their score and how MVPs are valued for their availability.

Importance of Continued Research & Next Steps

It's necessary to continue research and not consider a metric developed through this research as all-encompassing and without flaws. A metric designed to evaluate talent relative to peers and position is prone to a few issues and misconceptions. First, the metric may not be as well received by coaches and their staff as it is by the analytics community. The attempt to understand performances and statistics in new ways is an endeavor that is not necessarily shared by the entire sports community. Coaches may not see their players in a vacuum as their primary concern is success on the court. Because of this philosophy, they may not be interested in how a player performs alone, but as part of the team. While an individual metric such as this would seek to improve team-building efforts, presentation and refinement may still be needed to encourage buy-in.

Second, while this metric may seek to utilize readily available statistics to create an easier introduction to analytics, it will still use very rudimentary and simple statistics that might seem arbitrary. If using a traditional box score, there are five statistics that aid in offensive output (2-point shots, 3-point shots, free throws, assists, and offensive rebounds) while there are only three that affect defensive output (defensive rebounds, blocks, and steals). Two statistics are considered negatives to the offending team (turnovers, personal fouls) and do not necessarily aid offense or defense directly. Because of this disparity, more weight is given to offensive scoring and less to defensive scoring. The introduction of more data collection to analyze defensive skill sets can provide needed statistics that are not yet used widely.

Finally, it's important to divide up seasons based on eras, but when looking at more recent data, it becomes difficult to easily identify eras as they are occurring (Rocha da Silva, 2021). The modern NBA is very different from previous seasons in terms of play style and pace, but it would be ill-advised to attempt to define today's game in the same terms. The effectiveness of this metric would be best understood over time and through different eras to see how each position has evolved over different decades (Rocha da Silva, 2021).

Review of Literature

Key research exists on not only sports analytics, but the attempt to understand a player's value to their team in new and innovative ways. The following pieces of literature are not the basis by which this thesis' research was conducted, but they are important pieces that helped to shape the research questions and subsequent evaluation of different metrics. This review consists of sports analytics research at both the collegiate and professional level to create a baseline by which most programs operate. If a metric is successful at the professional level, then it stands to reason that it would be considered legitimate at other lower levels.

Basketball was not the only sport considered and individual player evaluation was not the only metric. Research into how a player's performance affects team performance is a key part of success for both the player and team (Chan et al., 2012). Special consideration was paid to research that looked at player value individually, but player value against team value was given legitimate merit. Finally, continued research into industry-standard metrics was valued highly. Elo, Pythagorean expected wins, and zero-sum game theory research were critical to understanding future metrics and the development of a metric here (Boudreaux, 2021).

Using Analytics to Study the Brigham Young University Football Program

Author Nelson Chung identifies three key theories in analytics and how they relate to Brigham Young University (BYU) football through his work in “The Brigham Young University Football Program and the Analytics Revolution” (2016). First are computer polls, which use margin of victory for each individual game, highlights how human error is important to eliminate when evaluating players (Chung, 2016). Instead of coaches and sportswriters ranking players through their own personal bias, computer polls can compare thousands of games throughout the season to present a valid argument for why one team might rank above another. Second is the “Blind Side” Thesis which, as Chung (2016) explains, is how players are interconnected to one another through their value. The most important position on the football field is the quarterback (Chung, 2016). As the sport continues to rely on passing more and more, the second most important position is the left tackle who is responsible for protecting the “blind side” of the quarterback. From there it’s clear that the right defensive end would be next as they’re responsible for beating that left tackle and sacking the quarterback. Every position is connected through their relationship to another.

Finally, recruiting is analyzed as possibly the most important aspect of determining success. College teams do not have the luxury of a draft where players, even possibly top-tier players, are made available on an even playing field. The worst teams in professional sports will likely draft higher and so have a better chance of selecting a great player (Chung, 2016). For colleges, they must stay competitive or find creative ways to entice players to join their programs. Chung uses excellent arguments to compare coaching staffs for BYU football and make the case that one coach is not necessarily worse than another based on their relative performance. While very specific theories are cited, they still present a compelling case for how we look at stats through different lenses. This project will follow a similar path and understand how player are evaluated based on their stats and why looking at players as positional players can help to build a better team through a better understanding of the information provided.

Meta-Analytics and The Benefit of Too Much Information

An important study in the field of analytics, Franks et al. (2016) compare existing metrics to help sort through the hundreds of options in their research "Meta-Analytics: Tools for Understanding the Statistical Properties of Sports Metric". Franks et al. utilize what they consider "meta-metrics" to sort metrics that provide stability, differentiation, and uniqueness (Franks et al., 2016). Through these three pieces of criteria, it's easy to see their effectiveness and how future metrics can adjust to stay relevant. First, stability is considered as it relates to the metrics' ability to track the same information over time. The analysis of one season can be difficult, especially as an outlier, but instead a player's performance over multiple seasons will provide more feedback on their ability.

Second, differentiation or discrimination, is important for large sample sizes and in determining players worthy of an award such as MVP in baseball (Franks et al., 2016). Finally, the independence of information by not looking at the metrics as individual pieces. Franks et al. explain that this is especially true for front offices to consider the full range of a player:

> "This is especially important for decision makers in sports management who use these metrics to inform decisions. Accurate assessments of player ability can only be achieved by appropriately synthesizing the available information. As such, we present

a method for quantifying the dependencies between metrics that can help decision makers make sense of the growing number of data summaries."

The use of a meta-analytics system to help value different metrics would have a profound impact on how we consider data (Franks et al., 2016). All three points should be carefully considered for the creation of a new metrics, paying careful consideration to how that metric would fit into the world.

The Rise of Advanced Analytics

Yago Colás, a professor at Oberlin College, covers a major challenge facing sports analytics and the ability to collect relevant data in his paper "The Culture of Moving Dots: Toward a History of County and of What Couns in Basketball" (2017). Traditional statistics rely on only visual cues and a distinct lack of technology other than the observer's ability to discern each category (Colás, 2017). Advanced analytics, and the ability to understand the game of basketball on a more fundamental level, requires technologies that are still emerging and do not yet have a metric tied to them. The ability to track player movements to understand something as basic as ball movement, but a factor of the sport that has yet to be quantified, is important (Yago Colás, 2017).

In a different capacity, digital technologies have changed the context of other statistics and represented a push to quantify the intangible. Colás goes even further to contextualize the "…shift toward quantitative thinking in basketball culture by emphasizing dimensions of the sport and ways of approaching it" (2017). The fascination, in his opinion, with quantifying everything in sports has led to a noticeable marginalization of the field as opinions differ greatly on the effective application of metrics. This opinion is vital to not only the research presented here, but to its future application.

The use of a highly specific metric that serves to only tell a new story, not create a new standard, should be met with caution. The use of analytics should be in a storytelling capacity and not strictly a decision-making capacity. Still, the use of digital technologies to gather increasingly specific data was not considered for this research out of respect for the availability of use of more traditional statistics.

Analysing the Play Beyond the Play in Hockey

An important study in the field of analytics, the research by Czuzoj-Shulman et al. (2019) titled “Winning Is Not Everything: A contextual analysis of hockey face-offs” takes careful consideration with respect to relative play value and not just the play at hand. Relating to the sport of hockey, win percentage on faceoffs are understood as more complicated than on the surface. The ability to win a faceoff and then position the puck in a situation that create a better scoring opportunity is an advanced way of looking at the sport. As Czuzoj-Shulman et al. explain, “…not all face-off wins are made equal: some players consistently create post-face-off value through clean wins and by directing the puck to high-value areas of the ice” (Czuzoj-Shulman et al., 2019). Their subsequent model creates a post-face-off value system to consider the “wins above expected” based on where the puck is placed on the ice.

The culmination of this data is valued as it relates to this research as it demonstrates how small situations can be cultivated to create a better understanding of more highly specific situations. This model also shows how the same statistic can be understood in a different way based on its added value. For this research, the value of a player’s hypothetical rebounding may not be equal to another’s based on game situation and position. While Czuzoj-Shulman et al. demonstrated the continued value of a clean faceoff win, this research would not be able to understand a player’s scoring as it relates to previous or subsequent plays. The totality of the statistics would be considered and compared to each other, not the individual statistic. The metric that Czuzoj-Shulman et al. created is valuable for understanding the added value of a player on the ice while this research would look at added value of a player over the course of a season and with respect to their position.

Real Application of Pythagorean Expected Wins

Boudreaux et al. (2021) examine Bill James' original Pythagorean Expected Wins Percentage Model in their paper titled “Application of the Pythagorean Expected Wins Percentage and Cross-Validation Methods in Estimating Team Quality” and two alternative contest theory models—the serial and difference-form CSFs. It was found that, on average, the serial CSF model for wins estimation noticeably improved the accuracy of team quality assessments (Boudreaux et al, 2021). The study serves as a practical test of distinct contest forms within a real-world context. By harnessing mathematical applications and contest theory insights, enhancements to the ability to estimate and predict team quality was evident. More importantly, the consistency of outcomes holds across various models and future endeavors could explore the comparative performance of the alternative models discussed within different sports leagues (Boudreaux et al, 2021).

The evaluation of Bill James’ revolutionary model in this research helps to shed light on the effectiveness of expected wins from the mean. This thesis will look closely at Pythagorean wins as well as game theory to determine how best to weigh player value against the average and how player performance compares to replacement-level players.

The Importance of Understanding Player Types in the NHL

The study titled “Quantifying the Contribution of NHL Player Types to Team Performance” by C.Y. Chan et al. (2012) utilizes what’s called “k-means clustering” to define distinct player categories for each of the three positions within a National Hockey League (NHL) team. C.Y. Chan et al. analyze and seek to establish a quantifiable relationship between a team’s performance and the player categories that have emerged from the clustering process (Chan et al. 2012). Their findings indicate that goalies play a predominant role in influencing team performance, with forwards ranking second in impact, followed by defensemen. These insights can be leveraged to scrutinize trades and their potential repercussions on team performance.

The relationship between statistics and value was explored heavily by Chan et al. (2012) and their findings show how the value of a particular player on team performance can play a huge role in contract values and team development from a front office perspective. After establishing the relative value of different positions, it’s clear that goalies are much more influential on their team’s success than other positions and would theoretically be one of the highest paid players on the team (Chan et al. 2012). Similarly, top-tier goalies should be more sought-after by front offices and should merit heavier consideration for individual awards.

Instead, we see that the position isn’t weighted in the eyes of the public in the same way that it should be which could have a negative effect on the winning percentage of a team. This research would also seek to understand which positions are the most effective but more specifically, which players are performing the best at their position.

Valuing Defensive Prowess Using Advanced Tracking Data

The importance of defensive statistics in basketball continues to be undervalued with respect to current metrics. Offensive play tends to be the measuring stick for a basketball player’s performance and stats like blocks, steals, and rebounds, are seen as supportive, not primary (Franks et al., 2015). Even with the addition of defensive statistics, they provide a limited view of a player’s defensive skill with certain factors such as spacing, length, and movement playing a larger role in many cases. As Franks et al. (2015) point out in their paper “Characterizing the spatial structure of defensive skill in professional basketball”, “the state of the art in defensive analytics remains qualitative, based on expert intuition and analysis that can be prone to human biases and imprecision.”

Digital tracking technologies are providing an avenue to resolving this issue but its complexities and ability to be quantified in an easily digestible way present roadblocks (Franks et al., 2015). Franks et al. cover different aspects of defensive metrics to create a new understanding of defensive player value. The importance of their research can't be understated as it related to this research. Player value can be found when looking at statistics in a new way, but also by incorporating data that is still emerging. Players are likely to be overlooked based on their position which can impact their potential as well as their chances of earning individual awards.

Understanding the Metrics Available for Player and Team Evaluation

Terner and Franks (2020), in their paper "Modeling Player and Team Performance in Basketball", examine methods for distinguishing team strategy and performance at the team level as well as, at the player level, the vast array of tools for evaluating talent. These tools include metrics for overall player value, defensive ability, shot modelling, and methods for understanding performance over multiple seasons via player production curves. Their belief is that basketball analytics will continue to move away from a focus on box-score based metrics and towards models for inferring underlying aspects of team and player performance. The continued research into player production over multiple seasons is critical, but the ability to extrapolate data for a single season can present unique insights. This research will be focused on overall player value as well as evaluating how defensive statistics can be valued equally to offensive statistics.

Terner and Franks (2020) take special notice that the more data that's made available and the introduction of newer methods of evaluation do not automatically lead to better insights. Understanding of the underlying stats will be an essential component of the future of basketball analytics and based on their own literature review, that need in advanced evaluation in sports remains largely unmet. They conclude that, although new data has enabled increasingly sophisticated methods for collection, many of the richest data sources are not openly available. Progress in statistical and machine learning methods for sports is hindered by the lack of publicly available data.

There is potential for enriching partnerships between data providers, professional leagues, and the analytics community with the introduction events hosted by professional leagues, such as the National Football League's "Big Data Bowl" and the NBA Hackathon. This research provides a comprehensive analysis that addresses the challenges, developments, and potential future directions in sports analytics, particularly focusing on basketball. It underscores the need for sophisticated methods, data accessibility, collaboration, and a deep understanding of underlying statistics to truly advance the field and extract valuable insights from the data-rich world of sports.

A Metric Designed Around Player Tracking Data

Scott Bruce (2016), in his paper "A scalable framework for NBA player and team comparisons using player tracking data", covers the utilization of player tracking data in basketball to improve the evaluation of player performance. His research proposes using Principal Component Analysis (PCA) to understand most of the variance in the data. A measure called the Statistical Diversity Index (SDI) is introduced to allow for quick comparisons of a player or team's statistics. Bruce highlights the applicability of this framework for personnel management and how SDI helps identify players with similar statistical profiles, aiding decisions in areas like salary negotiations, acquisitions, and player replacements.

These methods are practical for coaches and managers, enabling quick comparisons and informed decisions. New data, as Bruce (2016) points out, would be beneficial to future research to help keep these models updated. While player tracking data could be the future of sports analytics, it's still a technology that we've seen is restrictive and in its infancy. Salary negotiations would be irrelevant to a system that is centered on the college level, but the use of this research at the professional level would mean the opportunity to understand the value of elite players to their peers and team.

Creating Opportunities for Sports Metrics by Meeting in the Middle

There is a distinct challenge in presenting analytics in the field of soccer for two reasons. First is that there aren't a bevy of traditional stats associated with soccer and second is that, for that reason, many coaches are weary of using analytics to evaluate their players. Jan Van Haaren's (2021) research, "'Why Would I Trust Your Numbers?' On the Explainability of Expected Values in Soccer", bridges the gap between providing metrics that can be used in soccer as well as making them easy to use by a coaching staff by using expected outcomes based on shot location. This allows analysts to see how well players are placing the ball based on previous situations. This creates a model that is highly accurate as well as easy to explain to an audience that may not have much experience with this field.

Van Haaren (2021) assigns shot location using, "a feature vector that reflect s a fuzzy assignment of a shot to designated zones on the pitch that soccer practitioners use to convey tactical concepts and insights about the game." This method is based around core principles of shot placement and contrast with other approaches that use highly specific locations to help educate players. Since Van Haaren's approach is centered around education from a simplicity standpoint and geared towards introducing audiences to analytics gently, this approach is much better.

Key to this thesis' research is the ability to create a metric that would be easy to use, easy to adapt, and easy to present to a wide array of audiences depending on their skill level. A simplified approach allows for the real application of this metric in a potential game situation and not necessarily “after the fact”. If an active metric detailing who is performing the best at their position could be implemented, coaches could see in real time who exactly is the best performer on the court relative to their position and to the established game plan.

Based on these key pieces of literature, current metrics are used for both player and team evaluation but not all metrics are used equally and not all data is valued in the same way. There’s a significant movement towards desiring advanced analytics and player tracking data in the field to better understand how a player’s movement is informing their statistics (Franks et al., 2015). Until that data becomes more widely available, standard metrics are still defining how we understand sports. Pythagorean expected wins and zero-sum game theory are the basis for many metrics because of their history of use in a variety of sport and non-sport settings (Boudreaux, 2021).

Action Project: The Pomeroy Metric's Influences

The development of an evaluation metric was carefully considered after first understanding three current tools and not only their implementation, but their standing in the professional sports community; Wins Above Replacement (WAR), Elo, and the Ken Pomeroy College Basketball Ratings. All three answer the same question from a different point of view and, in a way, all three can help to inform one another to provide context.

We can't discuss top tools for player evaluation without first looking at its origins and that begins with sabermetrics or SABRmetrics and its godfather, Bill James. Famous for his early baseball writings while working as a night security guard at a pork and beans cannery, James attempted to answer early statistical questions through analysis. His approach to analytics was coined as "sabermetrics" as a reference to the Society for American Baseball Research (SABR) and is a foundation for analytics today. While sabermetrics as a study is confined to baseball, it was Billy Beane's "Moneyball" implementation that laid the groundwork for different clubs across different sports to invest in analytics research (Society for American Baseball Research, 2023).

Moneyball: The Art of Winning an Unfair Game, a 2004 book by Michael Lewis, highlights the Oakland Athletics baseball team and their implementation of sabermetrics by their general manager, Billy Beane. Baseball is still dominated by traditional understanding of how players perform, how teams are built, and how championships are won, but Beane was an early pioneer in understanding statistics in a different way. He felt that for a small market club like the Athletics, it was nearly impossible for them to sustain success against large teams like the New York Yankees or Boston Red Sox. In the words of Billy Beane, portrayed by Brad Pitt in the 2011 film "Moneyball", "The problem we're trying to solve is that There are rich teams and there are poor teams, then there's 50 feet of crap, and then there's us. It's an unfair game" (Lewis, 2013).

Wins Above Replacement (WAR)

One way to better understand a player's performance is by using WAR (wins above replacement), a tool that has been refined and developed over time. The original formula can be found in Appendix A, figure 1 and continues to evolve as sports change and a better understanding is gained of how accurate the tool is in evaluating players and teams. Currently, there are two major variations of WAR: bWAR and fWAR. bWAR (Appendix A, figure 2) is a unique formula developed by Baseball-Reference.com while fWAR (Appendix A, figure 3) is relative to Fangraphs. The major difference between these two when it comes to positional players is that bWAR uses DRS (Defensive Runs Saved) while fWAR uses UZR (Ultimate Zone Rating) where UZR considers three years of player ratings and DRS uses up to a year so ratings for rookies can be drastically different (Slowinski, 2023)

When it comes to pitchers, fWAR uses FIP (field independent pitching) to help level the playing field and focus on a pitcher's performance regardless of the skill of the defense behind them (Slowinski, 2023). bWAR utilizes RA9 (runs allowed over 9 innings) which accounts for any runs surrendered, earned or unearned (Baseball Reference, 2018). If two pitchers were to throw no-hitters but one struck out 15 batters and the other struck out zero, then bWAR would consider them nearly equal because the same outcome occurred. fWAR (and FIP by extension) would place more value on the pitcher that had a greater effect on their chance for success. While these are two varying schools of thought (product vs method), the possibility for understanding the same statistics in different ways can clearly have pros and cons.

First, using both fWAR and bWAR in harmony with one another can paint a better picture of a player's performance. WAR in general does a great job of valuing "complete players" who can make an impact in multiple ways. Comparing MLB & NBA players on both sides of the ball can showcase this clearly. At the midpoint of the 2023 season, perhaps the best non-pitching hitter in baseball is Ronald Acuña Jr. who boasts a slash line of .331/.408/.582 (2nd, 3rd, and 3rd, respectively) with 21 homeruns (T-11th), 55 RBIs (T-23rd), and 41 stolen bases (2nd). This is MVP-level trajectory and an excellent start to the season to earn a whopping 5.0 WAR, leading MLB. On the other side of the ball, one of the best non-hitting pitchers is Shane McClanahan who owns a 2.53 ERA (2nd among qualified players), 11-1 record (T-1st in Wins), and 101 strikeouts which has culminated in a 2.9 WAR (T-9th). Both players are having excellent seasons, but Acuña Jr.'s pitching WAR is 0.0 and McClanahan's hitting WAR is 0.0. When we look at a player like Shohei Ohtani who owns a pitching WAR of 2.5 and a hitting WAR of 4.0, we get an image of a player doing something we've never seen before. While he isn't the top hitter or pitcher in baseball, he is the 6th best hitter and 18th best pitcher by WAR. Performance like that does not happen in baseball which is why he is the obvious American League MVP candidate at this point in the 2023 season.

Basketball, where players are required to play offense and defense constantly, also shows the value of a players who excel at both ends of the floor. The 2022-23 MVP, Joel Embiid, finished the regular season averaging 33.1 PPG (1st), 10.2 RPG (10th), 4.2 APG, and 1.7 BPG (8th). Another MVP-candidate that season, Nikola Jokić, averaged 24.5 PPG (25th), 11.8 RPG (3rd), 9.8 APG (4th). Both players are centers in the NBA. The demands of modern sports are for players to be good across the board, not just one thing. While a traditional center rebounds well and scores in the paint, we're seeing those same requirements but to an extreme level. There is increasingly a desire for large players to be able to defend on the perimeter and score from 3-point range. Many of these players are drastic examples and showcase the best that the sport has to offer, but they are bucking a consistent trend and evidence that WAR is a unique tool for evaluating players based on their ability to "do more".

WAR is still a finicky measurement tool and as we've seen, there's little consensus on the finer applications. Since there is no standard, our understanding of WAR through bWAR and fWAR is evolving and so in their current form, small deviations can have a big impact on a player's rating (Slowinski, 2023; Baseball Reference, 2018). These tools are used by teams, scouts, analysts, and other sports evaluators to decide on the future of their teams and players (Ruiz, 2015). It's important that these tools are as accurate and reflective of the game in its current state while being mindful of the game as it has evolved over time to accurately compare players to one another. The definition of WAR, using relative value over "replacement level" players" can fail to account for a player relative to their peers and instead their value to an imaginary and average player that may not exist. WAR establishes what average is and players are compared to how they rank above or below that average whereas other tools like Elo ratings can better predict how two players compare to one another. Still, WAR is widely used as a determining metric when it comes to MVP voting for Major League Baseball and is valued specifically for its ability to set a baseline.

Elo Player Ratings

Elo (typically pronounced /iːloʊ/) ratings, named after Arpad Elo, a Hungarian physicist who wanted to improve the chess-rating system, a zero-sum game. The difference between two player's Elo ratings gives an indication of the outcome of the match. Two players with the same rating would theoretically have the same chance of success in a match, or the same number of wins in matches. Points are taken from or lost to opponents following a match to account for the zero-sum nature of many sports. Elo ratings (Appendix Figure 1) aren't meant to be considered for any match, but for a body of work. A player's true level is the sum of their performance over time and not for a specific match. The deviation from match to match may not seem extreme or sometimes even noticeable (Elo, 1966). The system also assumes that a player who wins the match made the best moves and not necessarily the best possible moves. In essence, they performed exactly as well as they needed to, given their opponent.

Elo (1966) naturally moves players towards the mean. Top-rated players can quickly be deemed overvalued and low-rated players can move upwards quickly based on a few performances. To be considered at the top or bottom of rankings, players need to consistently perform at that same level, but variations in performance can lead to movement that doesn't accurately reflect the player's true skill. In a theoretical sense, good players will maintain higher ratings as they defeat others, but the standard deviation can have a drastic effect with overall record. If player A, with a rating of 1000, player ten matches against other 1000-level players, their possible rating outcomes would be: 10-0: 1400 (Class C), 9-1: 1320 (Class D), 8-2: 1240 (Class D), 7-3: 1160 (Class E), 6-4: 1080 (Class E), 5-5: 1000 (Class E), 4-6: 920 (Class F), 3-7: 840 (Class F), 2-8: 760 (Class G), 1-9: 680 (Class G), 0-10: 600 (Class G).

A perfectly average performance (5-5) and even up to a very respectable performance (7-3) would make no difference to their rating class, while a slightly below average performance would drop them down a class rating or a terrible performance would drop them even further. In order to move up just one class or even two, it would require a nearly flawless to flawless performance. If player A went 4-6, dropping their rating to 920 and player B went 8-2, increasing their rating to 1240, they will both have moved a single class. For player A to reach player B's level, they would need to go 20-0 in 20 straight matches against 1000-level players. For player B to drop to player A's level of 920, it would require going 5-18 (915 rating) over 33 matches. A flawless performance over twenty matches compared to a subpar performance over thirty-three matches does not show relative movement. Elo (1966) makes it hard to see upward movement even with perfect performance as well as difficulty in moving downward even with prolonged poor performance. Winning early and often is the best way for players to quickly move up the rankings and stay there.

What Elo (1966) does very well is as a comparative ranking system among similar players. The goal is for players to, over time, be sorted and matched against others of similar skill. It doesn't consider their true skill but instead their relative skill. Matches against computers can better determine a player's ability to make the perfect moves at the right time while Elo focuses on measuring the bare minimum skill-level a player needs to win a match.

Elo (1966) assumes that all scenarios are zero-sum which prevents them from accurately evaluating players on many team sports where the individual game is zero-sum, but the performance of each player is not. Two players on opposing teams can have high-level performances but only one will be on the winning team (in the case of sports that don't allow for draws/ties). For chess, every move an opponent makes in their favor is a net negative while in baseball, a player could make a play in favor of their team, but not necessarily against their opponents personally. The ability to evaluate a player removed from their team and relative to other players is something that Elo in its purest form cannot accomplish as it doesn't factor in external factors that are difficult to quantify such as luck and strength of schedule.

Ken Pomeroy (KenPom) Rankings

Ken Pomeroy (2023) is the creator of the KenPom ranking metric which looks at NCAA Division I college basketball through a possessional lens (Pomeroy, 2023). Focusing on tempo and pace of play, KenPom is also unique in its ability to incorporate luck as a contributing factor by using Pythagorean expected wins. What's most important to KenPom is not only who a team plays (which affects their strength of schedule and strength of record) but also how efficient they are both on offense and defense (Franks et al., 2015). By using adjusted offensive and adjusted defensive efficiency, KenPom arrives at the core of its overall rankings with Adjusted Efficiency Margin by subtracting the defensive from the offensive.

The adjusted average illustrates roughly how many points a team should win above average (e.g., a value of +9.1 would mean that a team should win by 9.1 points over an average team).

Ken's ranking metric is unique in how it evaluates teams as a complete unit and in determining expected outcomes. While top offenses and defenses may appear in the same order on KenPom rankings, the efficiency by which these units perform is an indicator of how they will match up against other teams. Since these rankings are used to help determine winners during the NCAA Division I Men's Basketball tournament, it's important to utilize a metric that shows the relative strength of each team. Good teams should defeat bad teams by a larger margin than other good teams. This is a way of determining the relative value of each win. Additionally, the use of luck as a standard deviation from the expected helps to show which teams are overperforming or underperforming. While luck does not have a huge impact, it can help serve as a "momentum" metric to understand which teams are performing well based on unseen factors.

Two gaps that are evident in KenPom rankings, are rarity, are that they don't look at teams independent of one another. By comparing teams to one another through strength of schedule and victory, a ceiling and floor are set that can skew our understanding of the relative skill of a team from year to year. Since each year acts as its own set of data, it would be difficult to compare teams across as much as a decade due to the variances in performance. KenPom also doesn't look at streaks as a factor towards a team's future success. A top-tier team in terms of efficiency that is currently on a multiple game losing streak would have that information taken into account against a team that is on a multiple game winning streak. Still, KenPom would look at the scores of each of these teams throughout the season.

Finally, the strength of the team is considered and not the individual players. This can be seen as both an advantage and a disadvantage when determining a potential winner as recent changes in personnel can have a drastic impact that may not be evident. If a team has one of the best players in the country suffer an injury, they may still be considered a fantastic team in adjusted net efficiency, but a key reason why they have been one of the top teams all season was that player. It's impossible to re-evaluate the team through these metrics since the team is evaluated collectively. Nevertheless, the KenPom rankings are one of the premier tools for evaluating team talent and despite its long-tenured existence, is rapidly becoming a primary tool for college basketball analysis.

The Pomeroy Rankings Metric (Pomeroy Metric)

The Pomeroy Rankings Metric (not to be confused with Ken Pomeroy and KenPom Rankings) seeks to attack the gaps in previous metrics while also providing a new way of looking at traditional baseline statistics. Going through several iterations, the metric has evolved into its current form as a tool to compare high-level talent to one another both for players in the same position and for players across positions. Imagined as a tool for every sport that records statistics, it will only be used in its basketball form in this capacity. Specifically, it looks at the highest level of American basketball, the National Basketball Association (NBA) and the top-5 Most Valuable Player (MVP) vote getters since the 2010-2011 season.

This seemingly specific lens is not without a distinct purpose. It's important to evaluate not only players at the highest level of their respective sport, but looking at players who are considered to be the "best of the best." While the metric can be scaled to any level of play, including its intended target of small programs like SMWC, for the purposes of illustrating a clear point, the metric will start with the NBA. Liberty has been taken to illustrate this at the small college level using statistics from SMWC's men's and women's basketball programs, but these should be considered only demonstrative in nature.

The Metric's Evolution

In its original version, it was simply based off the author's own personal valuation metric. This was both flawed and intentional as the author should, in no way, be considered an authority on the valuation of basketball talent. Still, it was intended to demonstrate how a coach or front office could warp the metric to their liking based on their expert opinion. If, for example, a coach valued a center who could shoot from 3-point range, then the metric could bump that value up a little more. While this theory was a focal point of the original version, it could not be deemed sufficient for use at this time.

The second version of the metric was focused more on true statistics and comparing players relative to both their position and every other position. It's important to first find the multiplier for each box score statistic. For example, to find the 3-point multiplier for a point guard, first the average of all 3-pointers made by all players (3a) (140) is found and then the average of all 3-pointers made by just point guards (3pg) (182.9). The category multiplier = (3pg/3a) = 1.31. This formula will be followed for each category as defined below for point guards. Other positions are keyed as "sg" (shooting guard), "sf" (small forward), "pf" (power forward), and "c" (center).

3-pointers made – 3pg/3a

3- pointers missed – 3Mpg/3Ma

2-pointers made – 2pg/2a

2-pointers missed – 2Mpg/2Ma

Free throws made – FTpg/FTa

Free throws missed – FTMpg/FTMa

Offensive rebounds – ORBpg/ORBa

Defensive rebounds – DRBpg/DRBa

Assists – ASTpg/ASTa

Steals – STLpg/STLa

Blocks – BLKpg/BLKa

Turnovers – TOpg/TOa

Personal fouls – PFpg/PFa

Multipliers for each category and each position will then be used against individual players based on position. For example, in the attached Excel document, cell E11, the player recorded 128 3-pointers. His Pomeroy score for that category is the product of 128 and 1.31

to equal 167.4. This is continued for all categories. The raw Pomeroy score is the summation of all thirteen categories to equal, in cell S11, 182.9.

This may seem obvious for any position, but that's not the case. Other positional multipliers are, 1.31 for shooting guards, 1.05 for small forwards, 0.55 for power forwards, and 0.43 for centers. A point guard and a shooting guard making a three pointer are valued the same but a center making a three pointer is less valuable. This isn't to say that a center who makes a three isn't valuable in the context of the game, but in the context of MVP value. Centers who make threes don't see that value returned in the same way towards their ability to earn MVP votes as it would for a point guard or shooting guard.

In the third, and current version, it was clear that MVP winners could be valued based on their votes to help weight their statistics based on what voters determine is most important. While the unweighted version of the Pomeroy metric might disagree with which player should have been named MVP, it's important to re-evaluate the statistics based on what voters determine is most important to them including factors that may not be clear, quantifiable, or included in the unweighted statistics. (e.g., popularity, team record, momentum). The weighted formula was easily achieved by multiplying the unweighted Pomeroy score by a multiplier based on their votes won. If a player won 977 out of 1000 possible votes, their unweighted score would be multiplied by .977. Some years had more or less total votes which would allow the percentage to stay the same.

Notable Gaps

It's important to distinguish the language between current versions and a final version. There is no conceivable final version to the Pomeroy metric and improvements could always be made. Some noticeable gaps exist in the current version and it's critical to identify at least three of them that are the most impactful. First, the metric looks only at peak level players, not against the average. If a small program wanted to use this metric to evaluate the best possible talent that may be overlooked, they would need to place all possible players into the metric at once and all those players would need to be compared to someone else. Where other metrics, like WAR, look at players relative to the "average", the Pomeroy metric looks at players against the max.

If a women's basketball coach wanted to compare players for recruitment purposes, they would need to determine what they consider the "best" in their eyes. That could be award winners in their conference, award winners in their association, or even MVP-level performances at the highest level, the Women's National Basketball Association (WNBA). None of these choices would ultimately matter to the scores other than making them seem more inflated or depressed, but consistency is most important. If players are compared against their WNBA counterparts, they must always be compared against the WNBA. If a coach is more concerned with how those players would look in terms of winning awards in their conference, they should compare players against those statistics. Coaches may consider any comparisons to be more or less valuable based on how those awards are distributed and their perceived legitimacy (Bruce, 2016).

The second gap in the Pomeroy metric is that it does not utilize "zero sum" game theory found in Elo rankings. While in theory, the better one player performs means their odds of winning MVP increase which means that another player would be less likely to win MVP, Pomeroy scores look at players individually. A player's stats are compared against their predecessors, not their contemporaries. Because this metric looks at players in a vacuum, it's not possible to evaluate talent in a way that is very popular relative to game theory.

The final gap to address is that this metrics looks only at individual strengths and no team factors. Team record, strength of schedule, or even how a player performance affects the team in general are not considered. These factors are incredibly important when it comes to the success of a team and for coaches to build perennial winners. Coaching staffs may not value player in a vacuum and instead how they work with one another. It wouldn't necessarily be possible to pick out the top player at each position and combine them into one team with the expectation of success. Chemistry and team building are important factors that aren't quantifiable and come from external sources. The Pomeroy metric is about finding value as well as identifying top performers who otherwise might not have been considered.

The Pomeroy Metric in Action

To understand how the metric works and what conclusions can be drawn, we must look at the data sets as a whole and individually. The more modern the data, the more accurate it will be in predicting success. The current data set is fixed between the 2010-11 season and the 2022-23 season not only to use as a large enough reference, but to illustrate the fluid nature of this metric. Over time, the data set will need to be either trimmed or determined to be a permanent fixed amount of time. Either older seasons will need to be removed from consideration as new ones are added thus maintaining only a twelve-year period or a specific period (e.g., ten years, twenty years, etc.) will need to be established as the rotating data set. It's important to determine that amount of time to use, but that amount of time has not been determined during this research.

Looking at the data sets individually requires an effort to understand each player as well as their position. One-time MVPs are harder to track over the course of their career and even harder still are players who only garnered top-5 votes only once. Players such as LeBron James, Kevin Durant, and James Harden have appeared multiple times over the course of their careers so tracking their data as it relates to MVP-caliber performance is much easier. This allows for understanding how changes in their game affect their ability to win MVP and if there weren't any noticeable changes to their statistical output, then it shows how their game was valued relative to the rest of the league.

Raw vs Weighted Scores

A player's raw Pomeroy score is first calculated by establishing the time frame for consideration. Since this research kept the period from the 2010-11 season to the 2022-23 season, that will be the only range considered. Each of the top five MVP vote getters from that season have their standard box score statistics recorded including 3-pointers, 2-pointers, free throws, rebounds, assists, steals, blocks, turnovers, and personal fouls. For this range of data, 13 seasons, there are 90 players to consider. Each statistical category is then averaged (e.g., for 3-pointers, all three pointers made by these 90 players over the 13 seasons are averaged out). This provides a reference point for the average number of 3-pointers made by a top-5 NBA MVP vote getter over the past 13 seasons. This formula is continued for every statistical category until there is a 13-year average for each one.

The second step is to use the same calculation but only for specific player positions. For example, only the stats for point guards are averaged. The core of the metric is based around comparing the average for each position divided by the 13-year average to give a multiplier for each category. This shows the difference in statistics for a certain position against all other positions. That multiplier is then applied to the statistical category to give a raw Pomeroy score.

Finally, in order to calculate a weighted Pomeroy score, the raw score is multiplied by the numbers of points received in MVP voting that season. This score will almost always be a lower number unless a player receives 100% of first place votes then the scores will be the same. This weighted calculation factors in unknown voting considerations to help create an even larger disparity between a season's MVP and other player meriting consideration.

2010-11 NBA Top-5 MVP Vote Getters

The final Pomeroy Metric results for the 2010-11 season are shown in Appendix Figure 2. The first column shows how each player finished in actual MVP voting with

Derrick Rose capturing his first award. Each player's position is listed in the third column and from there each stat is divided into their own column. From left to right we see 3-pointers made (3P), 3-pointer missed (3PM), 2-pointers made (2P), 2-pointers missed (2PM), free throws made (FT), free throws missed (FTM), offensive rebounds (ORB), defensive rebounds (DRB), assists (AST), steals (STL), blocks (BLK), turnovers (TO), and personal fouls (PF). These do not encompass all possible stats recorded but are the basic stats available in a traditional box score. Finally, we have the multiplier which is a percentage of MVP votes received based on the number of voters.

3P
128
167.4
163.6

Each statistical column is split up into three sections for each player. The image to the right shows the 3-point category for Derrick Rose. The first line, 128, indicates how made 3-point shot he made during the season. The second line, 167.4, is the product of the first line and the point guard multiplier for 3-pointers made. Each position has their own multiplier which is the average of every player at the position against that category for every position. Finally, the third line is the product of the second line and the player's votes multiplier found in the 17th column of figure 2 (following the personal foul column). What the two lines reveal is that, based on other players at the position, the value of Derrick Rose's 3-pointers that season were about 1.31x higher than average to give a score of 167.4. Although, because of the number of MVP votes he received, it's dropped slightly to 163.6. The second line represents the Raw Pomeroy Score while the third line is the Weighted Pomeroy Score. The former tells how the stat compares to their peers while the latter tells how valued that stat is to MVP voters.

Not every category is valued the same and statistics that are negatives to a player's performance are typically reflected as a negative. 2-pointers missed, 3-pointers missed, free throws missed, turnovers, and personal fouls are calculated the same way but subtracted from one to give a net result. These stats are not simply inverted to maintain the value of ball handling for a player. It’s common for a point guard to handle the basketball more often so their tendency to commit turnovers is higher. Coaches will likely say that they are not going to interpret the increase in turnovers by their point guard as a reason to give their center more ball handling duties, but instead see it as a product of the position. The metric might even reward players with a positive score for their missed shots, turnovers, or fouls based on how it affects their ability to win MVP. In the Pomeroy Metric, point guards receive a positive multiplier for their missed 3-point shots at 0.28 and shooting guards are slightly higher at 0.32. While other positions lose points based on their missed 3-point shots, with centers being the highest at -0.53, the metric doesn’t want to discourage players who should be taking those shots from doing so.

In the same way, both guards have positive multipliers for turnovers (0.07 for point guards and 0.08 for shooting guards) and shooting guards and power forwards are two positions that have positive multipliers for personal fouls at 0.05 and 0.07, respectively. Both abnormalities are due to the nature of the positions but more importantly due to the stats of MVP-caliber performances. It’s clear to the voters that turnovers among guards is not critical to their chances and personal fouls are not critical to the MVP changes of shooting guards or power forwards.

2010-11 to 2013-14 NBA Season Analysis

The 2010-11 MVP, Chicago Bulls point guard Derrick Rose, received his first and only MVP award as he led his team to a 62-20 record and first place finish in the Central Division. His Raw Pomeroy score of 182.9 would place him third among the top-5 vote getters behind center Dwight Howard (262.9) and small forward LeBron James (190.3). While Rose may have been considered the better play overall, Howard played at a significantly higher level as a center than Rose did as a point guard. Relative to other MVP-level performances over the subsequent seasons, it's clear that Rose's performance was about average despite him running away with 977 points won.

The 2011-12 season saw LeBron James earn his third MVP award by narrowly beating out Kevin Durant. James' score of 152.6 was just half a point ahead of Durant's score of 152.1. Durant's scoring output was significantly higher but James' assists and steals outweighed Durant being named the scoring champion for the season. Durant's slightly higher turnovers and fouls also contributed to a slightly lower score. This season saw two players who had extremely strong claims to the MVP award despite James earning 888 votes to Durant's 735.

LeBron James (score of 209.9) would win his fourth MVP award the following season but being a nearly unanimous selection with 998 points to the second-place finisher Kevin Durant's score of 200.7 and earning 632 points. The most surprising finish this season was Kobe Bryant whose score of 175.3 would have placed him 3rd but instead he finished 5th and barely merited consideration with 152 points.

The 2013-14 season saw Kevin Durant winning his first MVP award, running away with the voting at 986 points. His well-rounded statistics may have contributed more to the team's success, but a surprising 3rd place finish of power forward Blake Griffin shows who had best positional season. Durant's score of 207.7 is less than that of Griffin's at 219.1 and even 4th place finisher Joakim Noah at 210.1. Griffin's performance this season was in fact a top 5 finish over the past 13 seasons by a power forward while Durant's was the best by a small forward. The value present in the power forward position compared to the small forward is significant as the best performance by a small forward over the last 13 seasons (Durant 2013-14) would rank 9th out of 12 for power forwards.

2014-15 to 2017-18 NBA Season Analysis

Following the 2014-15 season, point guard Stephen Curry would win his first MVP award with 922 points and a raw Pomeroy score of 180.4. James Harden however, a shooting guard, earns a score of 205.7, second among shooting guards in this 13-year period, and finishes in 2nd place. Harden outperformed Curry in nearly every category and despite having a higher rate of turnovers and personal fouls, was still statistically more significant. Curry's team, the Golden State Warriors, would finish with an impressive 67-15 record to Harden's Houston Rockets at 56-26 which likely led to Harden's 2nd-place finish. Anthony Davis, a power forward with the New Orleans Pelicans, would finish the season with a 203.0 Pomeroy score and should have earned more consideration than the 156 points he received from voters. IN fact, Curry's score of 180.4 was fourth among the top-five vote getters this season and likely benefited from team performance.

The 2015-16 season, Curry's second MVP award, was the first and only unanimous MVP award in league history as he helped lead his team to the best record in NBA history, but it was not the most impressive performance that season. His score of 198.3 was behind that of Russell Westbrook who continued to put up impressive numbers and a Pomeroy score of 221.3. Westbrook, a point guard with the Oklahoma City Thunder, would only receive 371 points towards the MVP award and was potentially he more valuable player to his team's success.

Russell Westbrook would finally earn MVP in the 2016-17 season after averaging a triple-double (double-digit points per game, rebounds per game, and assists per game), a feat which had only been done once 55 years prior. The performance gave him a Pomeroy score of 270.8, just a few points ahead of James Harden at 261.4. Harden would finish short of averaging a triple-double on the season and receive 753 points in the MVP voting to

Westbrook's 888. Westbrook's Pomeroy score of 270.8 is the highest score of the past 13 seasons regardless of position.

Harden would receive his first MVP award the following season with a Pomeroy score of 201.6 and 965 MVP votes. While he had a strong season, it wasn't his best season and based on Pomeroy scores, he ranked just fourth that season. Anthony Davis, with a Pomeroy score of 234.9 and LeBron James earned a 233.2 score to outpace Harden. Fifth-place finisher Russell Westbrook's score of 232.1 was only about a point behind James but Westbrook would receive 76 MVP votes to James' 738.

2018-19 to 2022-23 NBA Season Analysis

The 2018-10 season was Giannis Antetokounmpo's first MVP award and his Pomeroy score of 241.0 was the highest we've seen so far for power forwards and fifth best over this 13-year stretch, but it would be the second time that James Harden would record a top-5 Pomeroy score and finish 2nd in the MVP voting. Harden's score of 244.3 is just ahead of Antetokounmpo's.

2019-20 would see slightly deflated scores based on the NBA bubble and so a shortened season would have adverse effects. Giannis wins back-to-back awards, and this time has the highest score at 212.4 but James Harden would be snubbed with a third-place finish at 207.3 and just 367 points in the MVP voting. Surprisingly, small forward Kawhi Leonard would finish 5th in voting and a 128.6 Pomeroy score which is currently third lowest across all positions over this span and the lowest by a small forward.

Nikola Jokić, a center for the Denver Nuggets, would win his first MVP award in 2020-21 and the first center to win MVP since the 1990-2000 season. The center position appeared to have a resurgence with fellow center Joel Embiid finishing 2nd with a Pomeroy score of 150.0. Jokić's score of 220.4 was clear that he was the runaway favorite, and his 971 MVP points was real-world evidence of that. Embiid's Pomeroy score would be the lowest among centers during this span, showing just how difficult it is for centers to win the award despite strong seasons.

Jokić wins MVP again in the 2021-22 season and this time finishing closer to Joel Embiid with 875 and 706 MVP points, respectively. Jokić's 251.1 Pomeroy score and Embiid's 220.4 Pomeroy score reflect that vote disparity almost exactly. Giannis Antetokounmpo places third despite a higher score of 224.2 and Devin Booker a shooting guard with the Phoenix Suns, would finish 4th with a measly score of 136.0.

Finally, the 2022-23 season is where Joel Embiid breaks through and wins his first MVP award, finishing well ahead of Nikola Jokić but trailing him in Pomeroy score at 213.9 for Embiid and 224.6 for Jokić. Antetokounmpo finishes third again but with a higher score than Embiid at 215.7. In many ways, both Jokic and Embiid and less impressive seasons that the previous year but Jokić's was slightly more apparent which may have led to the voters awarding the MVP to Embiid.

Positional Evaluation

Each performance over the past 13 seasons is not made equal and does not deserve the same recognition (Czuzoj-Shulman, 2019). An MVP one season is not awarded based on the same criteria from previous seasons and should not be considered the basis for subsequent seasons. Players have been awarded MVP that, according to the Pomeroy metric, were weaker relative to one or two of their peers and there have been players who did not receive nearly the amount of MVP votes that they should have. The top performances of the past 13 seasons for each position have resulted in three of five winning MVP. The top three performances for each position have resulted in just five of fifteen winning MVP. Among point guards, Russell Westbrook's 2016-17 season was the greatest at the position but Stephen Curry's award in 2015 would put them on equal footing. Westbrook's raw score of

270.8 is currently the highest score among all positions and Curry's score of 180.4 would rank his performance as 37th out of 90 despite them being just two years apart.

Even in the same era, there can be extreme differences in what is considered relevant to MVP voting, but it's clear that team performance and potentially media exposure have the greatest impact (Chan et al., 2012). When considering MVP, it might be important to consider what the definition of "valuable" means and if a great performance on a bad team is less important that an average performance on a good team. The Pomeroy metric aims to remove other external factors and focus solely on a player's performance to determine which players are over or undervalued. Across other positions, we see similarities between Kevin Durant's MVP performance in 2014 with a score of 207.7 and LeBron James in 2012 with a score of 152.6. Even more stark is the difference between Giannis Antetokounmpo in 2019 (241.0) and the following year in 2020 (212.4). Not only is this the same position a year apart, but the same player. We saw a huge drop-off in his score but virtually no change in MVP voting as he earned 941 points in 2019 and even more at 962 in 2020. While it may appear that team success in the post season has a significant impact, voting is done at the conclusion of the regular season and has no effect.

It's clear that having an excellent season for your position doesn't necessarily result in an MVP award, but the weighted consideration of scores will influence the ability to potentially determine future player's chances (Deshpande, 2016).

Predicting Future MVPs

The use of this metric when predicting future performance has not been tested in a live setting but can be used with some success. Looking at the 2023-24 NBA season, player statistics can be updated after every contest and multiplied by an average weight of top-5 MVP winners by position. For point guards, their weighted points are 0.432 representing 432 points on average for the position. Shooting guards, small forwards, power forwards, and centers are weighted as 0.395, 0.465, 0.627, and 0.636 respectively. This can determine the potential votes a player will receive based on their position and illustrates key points. Namely, that centers are much more likely to merit MVP consideration than shooting guards if they bear the exact same statistics.

The value of centers who perform at a high level is much more evident than shooting guards. Centers, or “big men”, who can score and defend has shown to make a bigger impact on their MVP consideration than a shooting guard who tends to put up higher offensive numbers but lower on the defensive end. Other possibilities for determining future MVP based solely on individual performance is to compare average and median Pomeroy scores for top-5 players as well as MVP winners. The average Pomeroy score, across all positions, for MVP winners is 211.0 with a median of 209.9. The average Pomeroy score, across all positions, for top-5 MVP vote getters is 190.6 with a median of 180.4. While not all positions are weighed the same, an average score of about 210 is likely required to begin to merit consideration for MVP and an average score of 180-190 for top-5 based on this data. Over the past 13 seasons, the lowest Pomeroy score for a point guard to win MVP has been Stephen Curry in 2015 with 180.4 and can be considered the minimum to merit consideration. This analysis can be applied to all other positions to help determine a threshold. While many players have won MVP with much lower scores than the average of 210, we can see that the 200 range is MVP level in the Pomeroy metric.

SWOT Analysis

Strengths of the Pomeroy metric lie in its ability to compare players across positions based on how their stats affect MVP chances. By applying weight to each player’s stats based on their positional peers as well as all players placing in the top-5 of MVP vote getters, we can see how their performances stack up against one another. It also illustrates how statistics are valued by the MVP committee based on a player’s position and how some positions, like centers, are seeing a resurgence at the position as they're valued for their ability on both ends of the floor instead of one over the other. Other positions, like shooting guards are still seeing their skills limited to offensive output and despite some players putting up strong numbers, they will continue to be undervalued until the defensive output matches.

Weaknesses in the metric are clear as it uses simple and sometimes outdated box score statistics. To effectively understand the value of a player, we must go beyond their statistics, but these were not considered on purpose. Relying on averages can be ineffective as it presents numbers that are imaginary and do not represent real players. Finally, the metric provides a weighted score based on real world votes, but this is not considered the basis for research as it takes the determined Pomeroy score and relates to real world output, not vice versa.

Opportunities to improve and adjust the metric can be found in the changes from averages to medians to determine scores. Median statistics are real in nature and are not as skewed by performances above or below the ordinary. The use of the metric across more than a 13-year period can help to illustrate the evolution of the NBA over time and the ability to select different ranges of seasons can provide users the opportunity to apply their own eras to the research.

Threats to the Pomeroy metric are the misuse of the metric and remaining stagnant in approach. The continued updating of data and the refinement of the formula to better understand player performance by using tracking data will create new opportunities, but the inability to incorporate new data into the metric will quickly make it irrelevant and not useful for real-world application.

PESTLE Analysis of American Sports

To further understand how a new metric would be used, a PESTLE analysis of American Sports is needed to understand the current political, economic, social, technological, legal, and environmental situation (PESTLE analysis, 2023).While the entirety of the North American Sports environment is difficult to analyze, there are smaller scale groups such as the NBA and NCAA that can provide some insight in the possible success of the Pomeroy Metric.

Political

Political challenges may stem from the availability of foreign players in the United States and the application of the metric on players in different countries. The style of play for any sport in the United States is not necessarily the same as other countries so the translation of the statistic may be lost as certain traits are valued relative to the culture. Additionally, the use of the Pomeroy Metric in women's sports is a high concern as it would help to evaluate women's players in a new and unique way. It's important that new metrics aren't being controlled and promoted by one sport or gendered sport and instead are used by all.

Economic

The NBA is an $8 billion industry that features tv and streaming revenue as well as a desire for overseas expansion. The ability to evaluate players using the Pomeroy Metric at the professional level can potentially lead to not only more revenue but a more economic way of spending money on players that fit needs. At the college, and especially small college level, the need to use a metric that can save time, money, and additional resources can be invaluable as it provides a high-level of evaluation in a very accessible way.

Social

Social issues in professional sports, especially the NBA, through support for social justice and diversity, equity, and inclusion can have a major impact on the use of metrics. Players may be less receptive to metrics that define them through statistics alone and the use of advanced analytics as well as external factors such as camaraderie and locker room presence are all factors that need to be considered in harmony with any metric.

Technological

Technological issues stem out the wide range of metrics that are available and if there is a need for new metric at this time. With the growth of sports metrics in the sports community, there is a rapid and consistent desire for ways to understand the game and for any player, coach, institution, program, or league to gain a competitive edge through the use of proprietary information.

Legal

Legal roadblocks may include player health, betting, and labor issues. Professional, player incomes are predicated first on their availability and ability to stay healthy. Metrics that can provide insight into keeping players healthy and identifying when, if, or how a player needs to make changes to how they play the game, are invaluable. Sports betting is rapidly growing as it grows in legality across the U.S. and the need for fans to use tools to make informed and rational decisions can affect, for better or worse, how often they are successful in betting. Finally, labor disputes between players and the league can have a profound impact with the addition of analytics as front offices and owners can use statistics to make informed arguments in contract disputes.

Environmental

Environmental impacts of sports metrics are limited but growing artificial intelligence (A.I.) trends may lead to more advanced analytics by large computer systems. These systems can have negative impacts on the environment due to the large amounts of electricity that these systems demand.

Conclusion: Implementations and Implications

Small college athletic programs can't compete with their large counterparts due to a variety of factors including a lack of resources and a smaller footprint in the athletics landscape. The use of metrics can have a profound impact on the ability to level the playing field for those small programs and this can best be done by the creation of a new metric, the Pomeroy Metric, that uses MVP performance across positions to help find the best player value. If used by a small college athletics department, the Pomeroy Metric can be applied to different leagues, conferences, and divisions to help scale towards a specific player's ability to compete at different levels. Coaches can identify high school athletes who may not be recognized for their ability and the possibility of their skills translating to a higher level. Coaches can also identify current college players who are not being utilized in an effective way without only relying on film or in-person evaluation.

Theoretical Implementations

Implementation of the Pomeroy metric has been shown to be effective at the professional basketball level, but results at the collegiate level would likely still be evident. More data is needed to compare college players at the NAIA-level resulting in an effective analysis for Saint Mary-of-the-Woods College. An effort would need to be made to attain accurate and complete statistics of all All-Conference players in the River States Conference (RSC).

The use of the Pomeroy metric would aid in recruiting players as it helps to provide new context for player statistics and estimate how a recruit might perform in the RSC. Coaches would be able to insert a player's high school statistics to see how they would currently stack up against RSC competition as well as make comparisons against the current roster. If for example, a coach was interested in improving their depth at guard, the Pomeroy metric could be used to compare any number of high school guards against the conference to determine who would provide the most value. They could also see how the player would slot into the current roster to weigh the added value. Comparison of players is not the only implementation that can occur as the metric seeks to answer MVP discussions.

Which player wins MVP and which player should have won MVP are common questions and ones that are difficult to argue. While two players of the same position may be easy to compare, players across different positions are difficult. With team record not being considered, the Pomeroy metric serves to help answer those questions for players individually. The metric can be taken even further to help decide who the best player of all-time might be, although comparing statistics across long periods of time and different eras is not ideal and difficult to quantify (Rocha da Silva, 2021).

Future Implications

The implications of this metric can extend beyond the narrow scope of this research and be applied to other professional basketball leagues as well as sports. Applying this metric to WNBA MVPs will yield similar results. The metric can be adjusted and applied to different sports based on their top award winners. Since basketball uses the least number of players at one time versus other major North American sports like baseball, football, hockey, and soccer, the use of the metric would provide much more information for teams looking to find value as they are evaluating more players. Relevant statistics would need to be established for each sport based on their respective box scores.

Finally, the long-term implications could be found in the ability to apply the core principles of this metric to all statistic-recording sports. If the statistics for each sport are found to be relatively similar between one another, it would allow the metric to compare players from different sports to one another. The performance of a professional point guard in basketball and the performance of a professional third baseman in baseball could be compared, still relative to their sport and position. The future of the Pomeroy metric is to see a marked increase in the recruiting efforts of small colleges like Saint Mary-of-the-Woods and to provide a valuable tool for coaches and their staff who seek value where others may have missed.

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Appendix A – Formulas

$$\textbf{Performance rating} = \frac{\textbf{Total of opponents' ratings} + 400 \times (\textbf{Wins} - \textbf{Losses})}{\textbf{Games}}$$

FIGURE 1 – THE FORMULA FOR CALCULATING A PLAYER'S ELO RATING (ELO, 1966)

$$bWAR = (P_{runs} - A_{runs}) + (A_{runs} - R_{runs})$$

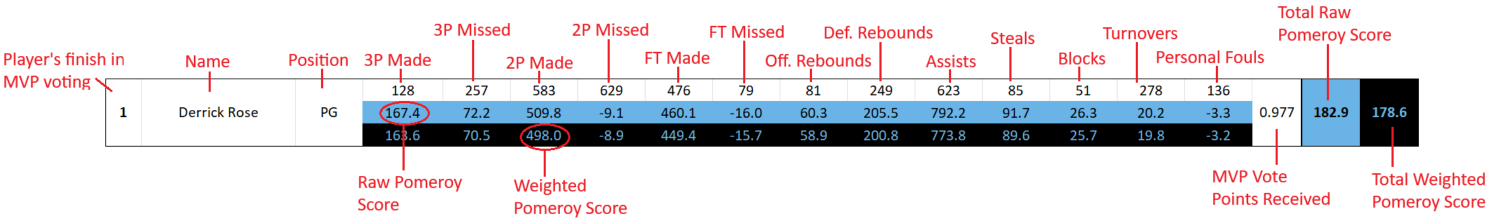
FIGURE 2 – CALCULATION OF WAR BY BASEBALL-REFERENCE (BASEBALL REFERENCE, 2013)

$$fWAR = wRAA + UZR + Position + \frac{20}{600} * PA$$

FIGURE 3 – CALCULATION OF WAR BY FANGRAPHS (SLOWINSKI, 2023)

Appendix B – The Pomeroy Metric

Key



Note: The table at the top of the first page titled “Pomeroy Rankings” are the multiplier values as discussed on page 42.

Note: The “Total Raw Pomeroy Score” is the summation of all Raw Pomeroy score values in columns 4-16 (highlighted as blue background with black lettering). The “Total Weighted Pomeroy Score” is the summation of all Weighted Pomeroy Score values in columns 4-16 (highlighted as black background with blue lettering). These formulas are discussed on page 43.

	Pomeory Rankings												
	3P	3PM	2P	2PM	FT	FTM	ORB	DRB	AST	STL	BLK	TO	PF
PG	1.31	0.28	0.87	-0.01	0.97	-0.20	0.74	0.83	1.27	1.08	0.52	0.07	-0.02
SG	1.31	0.32	0.90	-0.09	1.18	-0.14	0.63	0.71	0.98	1.05	0.65	0.08	0.05
SF	1.05	0.02	1.03	0.05	1.01	-0.09	0.73	1.02	0.82	1.04	1.09	-0.06	-0.14
PF	0.55	-0.38	1.23	0.06	0.98	0.56	1.36	1.24	0.81	0.86	1.58	-0.08	0.07
C	0.43	-0.53	1.07	-0.06	0.96	0.13	1.97	1.37	0.89	0.85	1.64	-0.05	0.19

Top Five NBA Regular Season MVP Vote Getters | 2010-11

Rank	Player	Pos	3P	3PM	2P	2PM	FT	FTM	ORB	DRB	AST	STL	BLK	TO	PF	Multiplier	Raw	Weighted
			128	257	583	629	476	79	81	249	623	85	51	278	136			
1	Derrick Rose	PG	167.4	72.2	509.8	-9.1	460.1	-16.0	60.3	205.5	792.2	91.7	26.3	20.2	-3.3	0.977	182.9	178.6
			163.6	70.5	498.0	-8.9	449.4	-15.7	58.9	200.8	773.8	89.6	25.7	19.8	-3.2			
			0	7	619	418	546	370	309	789	107	107	186	279	258			
2	Dwight Howard	C	0.0	-3.7	664.9	-26.8	522.0	47.9	607.5	1080.3	95.4	91.2	305.0	-14.7	49.2	0.531	262.9	139.7
			0.0	-2.0	353.3	-14.3	277.4	25.5	322.8	574.1	50.7	48.5	162.1	-7.8	26.1			
			92	187	666	540	503	160	80	510	554	124	50	284	163			
3	LeBron James	SF	96.7	3.8	682.8	28.9	509.3	-14.5	58.2	520.5	452.5	128.8	54.6	-16.7	-23.1	0.431	190.9	82.4
			41.7	1.6	294.5	12.5	219.7	-6.3	25.1	224.6	195.2	55.5	23.6	-7.2	-10.0			
			115	126	625	33	483	100	83	336	388	99	12	243	172			
4	Kobe Bryant	SG	150.8	40.2	561.6	-3.1	569.9	-13.7	52.6	238.9	380.8	103.6	7.7	20.3	8.9	0.354	163.0	57.6
			53.3	14.2	198.6	-1.1	201.6	-4.8	18.6	84.5	134.7	36.7	2.7	7.2	3.1			
			145	269	566	558	594	81	57	476	214	88	76	218	159			
5	Kevin Durant	SF	152.3	5.4	580.2	29.9	601.5	-7.4	41.5	485.8	174.8	91.4	83.0	-12.8	-22.5	0.157	169.5	26.6
			23.9	0.8	91.1	4.7	94.4	-1.2	6.5	76.3	27.4	14.3	13.0	-2.0	-3.5			

Top Five NBA Regular Season MVP Vote Getters | 2011-12

Rank	Player	Pos	3P	3PM	2P	2PM	FT	FTM	ORB	DRB	AST	STL	BLK	TO	PF	Multiplier	Raw	Weighted
			54	95	567	453	387	115	94	398	387	115	50	213	96			
1	LeBron James	SF	56.7	1.9	581.3	24.3	391.9	-10.4	68.4	406.2	316.1	119.4	54.6	-12.5	-13.6	0.888	152.6	135.5
			50.4	1.7	515.9	21.5	347.8	-9.3	60.7	360.6	280.6	106.0	48.5	-11.1	-12.1			
			133	211	510	443	431	70	40	487	231	88	77	248	133			
2	Kevin Durant	SF	139.7	4.2	522.8	23.7	436.4	-6.4	29.1	497.0	188.7	91.4	84.1	-14.6	-18.8	0.735	152.1	111.8
			102.7	3.1	384.1	17.4	320.6	-4.7	21.4	365.2	138.6	67.1	61.8	-10.7	-13.8			
			79	134	346	331	260	42	42	171	543	152	4	124	138			
3	Chris Paul	PG	103.3	37.7	302.6	-4.8	251.3	-8.5	31.3	141.2	690.5	164.1	2.1	9.0	-3.4	0.318	132.0	42.0
			32.9	12.0	96.2	-1.5	79.9	-2.7	9.9	44.9	219.6	52.2	0.7	2.9	-1.1			
			87	200	487	562	381	70	66	247	264	69	18	204	105			
4	Kobe Bryant	SG	114.1	63.8	437.6	-53.3	449.5	-9.6	41.8	175.6	259.1	72.2	11.6	17.0	5.4	0.290	121.9	35.4
			33.1	18.5	126.9	-15.5	130.4	-2.8	12.1	50.9	75.2	21.0	3.4	4.9	1.6			
			14	47	413	416	227	57	22	149	463	57	5	153	75			
5	Tony Parker	PG	18.3	13.2	361.1	-6.0	219.4	-11.6	16.4	123.0	588.7	61.5	2.6	11.1	-1.8	0.274	107.4	29.4
			5.0	3.6	98.8	-1.6	60.0	-3.2	4.5	33.6	161.0	16.8	0.7	3.0	-0.5			

Top Five NBA Regular Season MVP Vote Getters | 2012-13																	
			103	151	662	438	403	132	97	513	551	129	67	226	110		
1	LeBron James	PF	56.4	-56.8	811.4	27.3	393.4	74.6	131.6	637.3	447.4	111.0	106.2	-19.0	7.3	0.998	209.9	209.3
			56.3	-56.7	809.3	27.3	392.4	74.4	131.3	635.7	446.2	110.7	105.9	-19.0	7.3		
			139	195	592	507	679	71	46	594	374	116	105	280	143		
2	Kevin Durant	SF	146.0	3.9	606.9	27.1	687.6	-6.5	33.5	606.2	305.5	120.4	114.7	-16.5	-20.3	0.632	200.7	126.9
			92.3	2.5	383.7	17.2	434.7	-4.1	21.2	383.3	193.1	76.1	72.5	-10.4	-12.8		
			157	257	512	563	425	87	134	326	171	52	32	175	205		
3	Carmelo Anthony	PF	86.0	-96.7	627.5	35.1	414.9	49.1	181.8	405.0	138.8	44.7	50.7	-14.7	13.6	0.393	148.9	58.5
			33.8	-38.0	246.3	13.8	162.9	19.3	71.4	159.0	54.5	17.6	19.9	-5.8	5.3		
			76	156	336	288	286	37	53	209	678	169	10	159	143		
4	Chris Paul	PG	99.4	43.8	293.8	-4.2	276.4	-7.5	39.5	172.5	862.1	182.4	5.2	11.6	-3.5	0.239	151.7	36.2
			23.7	10.5	70.2	-1.0	66.0	-1.8	9.4	41.2	205.9	43.6	1.2	2.8	-0.8		
			132	275	606	582	525	101	66	367	469	106	25	287	173		
5	Kobe Bryant	SG	173.0	87.7	544.5	-55.2	619.5	-13.8	41.8	260.9	460.3	111.0	16.1	24.0	9.0	0.152	175.3	26.7
			26.3	13.3	82.8	-8.4	94.2	-2.1	6.4	39.7	70.0	16.9	2.5	3.6	1.4		

Top Five NBA Regular Season MVP Vote Getters | 2013-14																	
			192	299	657	540	703	102	58	540	445	103	59	285	174		
1	Kevin Durant	SF	201.7	6.0	673.5	28.9	711.9	-9.3	42.2	551.1	363.5	106.9	64.4	-16.8	-24.7	0.986	207.7	204.7
			198.8	5.9	663.8	28.5	701.6	-9.1	41.6	543.2	358.3	105.4	63.5	-16.5	-24.3		
			116	190	651	396	439	146	81	452	488	121	26	270	126		
2	LeBron James	PF	63.6	-71.5	797.9	24.7	428.5	82.5	109.9	561.5	396.2	104.1	41.2	-22.7	8.4	0.713	194.2	138.4
			45.3	-51.0	568.7	17.6	305.5	58.8	78.3	400.3	282.4	74.2	29.4	-16.2	6.0		
			12	32	706	609	482	192	192	565	309	92	51	224	265		
3	Blake Griffin	PF	6.6	-12.0	865.3	38.0	470.5	108.4	260.5	701.9	250.9	79.2	80.8	-18.8	17.6	0.347	219.1	76.1
			2.3	-4.2	300.4	13.2	163.4	37.6	90.5	243.7	87.1	27.5	28.1	-6.5	6.1		
			0	2	380	418	247	88	282	618	431	99	121	194	245		
4	Joakim Noah	C	0.0	-1.1	408.2	-26.8	236.2	11.4	554.4	846.2	384.2	84.4	198.4	-10.3	46.7	0.258	210.1	54.1
			0.0	-0.3	105.1	-6.9	60.8	2.9	142.8	218.0	99.0	21.7	51.1	-2.6	12.0		
			177	306	372	350	576	89	61	283	446	115	29	265	177		
5	James Harden	SG	232.0	97.6	334.3	-33.2	679.6	-12.2	38.7	201.2	437.7	120.4	18.7	22.1	9.2	0.068	165.1	11.2
			15.8	6.6	22.7	-2.3	46.2	-0.8	2.6	13.7	29.8	8.2	1.3	1.5	0.6		

Top Five NBA Regular Season MVP Vote Getters | 2014-15																	
			286	360	367	328	308	29	56	285	619	163	16	249	158		
1	Stephen Curry	PG	374.1	101.2	320.9	-4.7	297.7	-5.9	41.7	235.3	787.1	175.9	8.3	18.1	-3.9	0.922	180.4	166.3
			344.8	93.2	295.7	-4.4	274.3	-5.4	38.4	216.8	725.3	162.1	7.6	16.7	-3.6		
			208	347	439	476	715	109	75	384	565	154	60	321	208		
2	James Harden	SG	272.7	110.7	394.5	-45.2	843.6	-14.9	47.5	273.0	554.5	161.2	38.7	26.8	10.8	0.720	205.7	148.1
			196.3	79.7	284.0	-32.5	607.4	-10.8	34.2	196.6	399.2	116.1	27.9	19.3	7.8		
			120	219	504	436	375	153	51	365	511	109	49	272	135		
3	LeBron James	SF	126.1	4.4	516.7	23.3	379.7	-13.9	37.1	372.5	417.4	113.2	53.5	-16.0	-19.1	0.425	153.5	65.2
			53.5	1.9	219.4	9.9	161.2	-5.9	15.8	158.2	177.2	48.1	22.7	-6.8	-8.1		
			86	202	541	642	546	108	124	364	574	140	14	293	184		
4	Russell Westbrook	PG	112.5	56.8	473.1	-9.3	527.7	-21.9	92.3	300.5	729.9	151.1	7.2	21.3	-4.5	0.271	187.4	50.7
			30.5	15.4	128.1	-2.5	142.9	-5.9	25.0	81.3	197.6	40.9	2.0	5.8	-1.2		
			1	11	641	546	371	90	173	523	149	100	200	95	141		
5	Anthony Davis	PF	0.5	-4.1	785.6	34.1	362.2	50.8	234.7	649.8	121.0	86.0	316.9	-8.0	9.4	0.156	203.0	31.7
			0.1	-0.6	122.7	5.3	56.6	7.9	36.7	101.5	18.9	13.4	49.5	-1.2	1.5		

Top Five NBA Regular Season MVP Vote Getters | 2015-16

			402	484	403	309	363	37	68	362	527	169	15	262	161			
1	Stephen Curry	PG	525.9	136.0	352.4	-4.5	350.8	-7.5	50.6	298.8	670.1	182.4	7.7	19.1	-3.9	1.000	198.3	198.3
			525.9	136.0	352.4	-4.5	350.8	-7.5	50.6	298.8	670.1	182.4	7.7	19.1	-3.9			
			129	162	422	377	292	42	95	398	186	128	71	105	133			
2	Kawhi Leonard	SF	135.5	3.3	432.6	20.2	295.7	-3.8	69.1	406.2	151.9	132.9	77.5	-6.2	-18.8	0.484	130.5	63.1
			65.6	1.6	209.3	9.8	143.1	-1.8	33.4	196.6	73.5	64.3	37.5	-3.0	-9.1			
			87	195	650	484	359	132	111	454	514	104	49	249	143			
3	LeBron James	SF	91.4	3.9	666.4	25.9	363.5	-12.0	80.7	463.4	419.9	108.0	53.5	-14.7	-20.3	0.482	171.5	82.6
			44.0	1.9	320.9	12.5	175.1	-5.8	38.9	223.2	202.2	52.0	25.8	-7.1	-9.8			
			101	240	555	548	465	108	145	481	834	163	20	342	200			
4	Russell Westbrook	PG	132.1	67.4	485.3	-7.9	449.4	-21.9	108.0	397.0	1060.5	175.9	10.3	24.9	-4.9	0.371	221.3	82.1
			49.0	25.0	180.0	-2.9	166.7	-8.1	40.1	147.3	393.4	65.3	3.8	9.2	-1.8			
			186	295	512	388	447	51	45	544	361	69	85	250	137			
5	Kevin Durant	SF	195.4	5.9	524.9	20.8	452.6	-4.6	32.7	555.2	294.9	71.6	92.8	-14.7	-19.4	0.112	169.9	19.1
			21.9	0.7	58.9	2.3	50.8	-0.5	3.7	62.3	33.1	8.0	10.4	-1.7	-2.2			

Top Five NBA Regular Season MVP Vote Getters | 2016-17

			200	383	624	734	710	130	137	727	840	132	31	438	190			
1	Russell Westbrook	PG	261.6	107.6	545.7	-10.6	686.2	-26.4	102.0	600.1	1068.1	142.5	16.0	31.9	-4.6	0.888	270.8	240.5
			232.3	95.6	484.5	-9.4	609.4	-23.4	90.6	532.9	948.5	126.5	14.2	28.3	-4.1			
			262	494	412	365	746	135	95	564	907	121	38	464	215			
2	James Harden	PG	342.7	138.8	360.3	-5.3	721.0	-27.4	70.7	465.6	1153.3	130.6	19.6	33.8	-5.3	0.753	261.4	196.9
			258.1	104.5	271.3	-4.0	542.9	-20.6	53.3	350.6	868.5	98.3	14.8	25.4	-4.0			
			147	240	489	436	469	64	80	350	260	133	55	154	122			
3	Kawhi Leonard	SF	154.4	4.8	501.3	23.3	474.9	-5.8	58.2	357.2	212.4	138.1	60.1	-9.1	-17.3	0.500	150.2	75.1
			77.2	2.4	250.7	11.7	237.5	-2.9	29.1	178.6	106.2	69.0	30.0	-4.5	-8.6			
			124	218	612	390	358	173	97	542	646	92	44	303	134			
4	LeBron James	SF	130.3	4.4	627.4	20.9	362.5	-15.7	70.6	553.2	527.7	95.5	48.0	-17.8	-19.0	0.333	183.7	61.2
			43.4	1.5	208.9	7.0	120.7	-5.2	23.5	184.2	175.7	31.8	16.0	-5.9	-6.3			
			245	401	437	390	590	59	43	162	448	70	13	210	167			
5	Isaiah Thomas	PG	320.5	112.7	382.1	-5.6	570.2	-12.0	32.0	133.7	569.7	75.6	6.7	15.3	-4.1	0.081	169.0	13.7
			26.0	9.1	31.0	-0.5	46.2	-1.0	2.6	10.8	46.1	6.1	0.5	1.2	-0.3			

Top Five NBA Regular Season MVP Vote Getters | 2017-18

			265	457	386	341	624	103	41	348	630	126	50	315	169			
1	James Harden	SG	347.4	145.7	346.9	-32.4	736.3	-14.1	26.0	247.4	618.3	131.9	32.3	26.3	8.8	0.965	201.6	194.5
			335.2	140.6	334.7	-31.2	710.5	-13.6	25.1	238.8	596.6	127.3	31.1	25.4	8.4			
			149	257	708	466	388	143	97	612	747	116	71	347	136			
2	LeBron James	PF	81.6	-96.7	867.7	29.1	378.8	80.8	131.6	760.3	606.5	99.8	112.5	-29.2	9.0	0.738	233.2	172.1
			60.2	-71.4	640.4	21.5	279.5	59.6	97.1	561.1	447.6	73.7	83.0	-21.5	6.7			
			55	107	725	575	495	103	187	645	174	115	193	162	159			
3	Anthony Davis	PF	30.1	-40.3	888.6	35.9	483.2	58.2	253.7	801.3	141.3	99.0	305.9	-13.6	10.6	0.445	234.9	104.5
			13.4	-17.9	395.4	16.0	215.0	25.9	112.9	356.6	62.9	44.0	136.1	-6.1	4.7			
			227	402	394	392	493	45	62	263	481	77	27	206	117			
4	Damian Lillard	PG	297.0	113.0	344.5	-5.7	476.5	-9.1	46.2	217.1	611.6	83.1	13.9	15.0	-2.9	0.207	169.2	35.0
			61.5	23.4	71.3	-1.2	98.6	-1.9	9.6	44.9	126.6	17.2	2.9	3.1	-0.6			
			97	229	660	701	417	149	152	652	820	147	20	381	200			
5	Russell Westbrook	PG	126.9	64.4	577.1	-10.1	403.0	-30.2	113.2	538.2	1042.7	158.7	10.3	27.7	-4.9	0.076	232.1	17.6
			9.6	4.9	43.9	-0.8	30.6	-2.3	8.6	40.9	79.2	12.1	0.8	2.1	-0.4			

Top Five NBA Regular Season MVP Vote Getters | 2018-19

			52	151	669	375	500	186	159	739	424	92	110	268	232			
1	Giannis Antetokounmpo	PF	28.5	-56.8	819.9	23.4	488.1	105.0	215.7	918.1	344.2	79.2	174.3	-22.5	15.4	0.941	**241.0**	**226.8**
			26.8	-53.5	771.6	22.0	459.3	98.9	203.0	863.9	323.9	74.5	164.0	-21.2	14.5			
			378	650	465	416	754	104	66	452	586	158	58	387	244			
2	James Harden	PG	494.5	182.7	406.6	-6.0	728.7	-21.1	49.1	373.1	745.2	170.5	30.0	28.2	-6.0	0.776	**244.3**	**189.6**
			383.7	141.7	315.5	-4.7	565.5	-16.4	38.1	289.5	578.2	132.3	23.2	21.9	-4.6			
			292	465	415	442	453	87	105	523	318	170	34	205	214			
3	Paul George	SF	306.8	9.3	425.4	23.7	458.7	-7.9	76.4	533.8	259.8	176.5	37.1	-12.1	-30.3	0.356	**173.6**	**61.8**
			109.2	3.3	151.5	8.4	163.3	-2.8	27.2	190.0	92.5	62.8	13.2	-4.3	-10.8			
			83	187	533	403	289	63	228	637	580	108	55	248	228			
4	Nikola Jokić	C	36.0	-100.0	572.5	-25.9	276.3	8.2	448.2	872.2	517.1	92.1	90.2	-13.1	43.5	0.212	**216.7**	**45.9**
			7.6	-21.2	121.4	-5.5	58.6	1.7	95.0	184.9	109.6	19.5	19.1	-2.8	9.2			
			354	456	278	252	263	24	45	324	361	92	25	192	166			
5	Stephen Curry	PG	463.1	128.1	243.1	-3.6	254.2	-4.9	33.5	267.4	459.0	99.3	12.9	14.0	-4.1	0.175	**150.9**	**26.4**
			81.0	22.4	42.5	-0.6	44.5	-0.9	5.9	46.8	80.3	17.4	2.3	2.4	-0.7			

Top Five NBA Regular Season MVP Vote Getters | 2019-20

			89	204	596	349	398	231	140	716	354	61	66	230	195			
1	Giannis Antetokounmpo	PF	48.8	-76.8	730.5	21.8	388.5	130.5	190.0	889.5	287.4	52.5	104.6	-19.3	13.0	0.962	**212.4**	**204.3**
			46.9	-73.8	702.7	21.0	373.8	125.5	182.7	855.7	276.5	50.5	100.6	-18.6	12.5			
			148	277	495	383	264	117	66	459	684	78	36	261	118			
2	LeBron James	PG	193.6	77.8	432.9	-5.5	255.2	-23.7	49.1	378.9	869.8	84.2	18.6	19.0	-2.9	0.753	**180.5**	**135.9**
			145.8	58.6	325.9	-4.2	192.1	-17.9	37.0	285.3	654.9	63.4	14.0	14.3	-2.2			
			299	544	373	298	692	108	70	376	512	125	60	308	227			
3	James Harden	SG	392.0	173.5	335.2	-28.3	816.5	-14.8	44.4	267.3	502.5	130.8	38.7	25.7	11.8	0.367	**207.3**	**76.1**
			143.9	63.7	123.0	-10.4	299.7	-5.4	16.3	98.1	184.4	48.0	14.2	9.4	4.3			
			171	370	410	304	426	136	78	495	538	62	14	260	153			
4	Luka Dončić	PG	223.7	104.0	358.5	-4.4	411.7	-27.6	58.1	408.6	684.1	66.9	7.2	18.9	-3.7	0.200	**177.4**	**35.5**
			44.7	20.8	71.7	-0.9	82.3	-5.5	11.6	81.7	136.8	13.4	1.4	3.8	-0.7			
			123	202	409	399	356	46	54	348	280	103	33	149	113			
5	Kawhi Leonard	SF	129.2	4.1	419.3	21.4	360.5	-4.2	39.3	355.2	228.7	106.9	36.0	-8.8	-16.0	0.168	**128.6**	**21.6**
			21.7	0.7	70.4	3.6	60.6	-0.7	6.6	59.7	38.4	18.0	6.1	-1.5	-2.7			

Top Five NBA Regular Season MVP Vote Getters | 2020-21

			92	145	640	416	342	52	205	575	599	95	48	222	192			
1	Nikola Jokić	C	39.9	-77.5	687.5	-26.7	327.0	6.7	403.0	787.3	534.0	81.0	78.7	-11.7	36.6	0.971	**220.4**	**214.1**
			38.8	-75.3	667.5	-25.9	317.5	6.5	391.3	764.5	518.5	78.6	76.4	-11.4	35.5			
			58	96	403	342	471	77	113	426	145	50	69	159	123			
2	Joel Embiid	C	25.2	-51.3	432.9	-21.9	450.3	10.0	222.1	583.3	129.3	42.6	113.1	-8.4	23.5	0.586	**150.0**	**87.9**
			14.8	-30.1	253.7	-12.9	263.9	5.8	130.2	341.8	75.7	25.0	66.3	-4.9	13.7			
			337	464	321	243	362	33	29	316	363	77	8	213	119			
3	Stephen Curry	PG	440.9	130.4	280.7	-3.5	349.9	-6.7	21.6	260.8	461.6	83.1	4.1	15.5	-2.9	0.453	**156.6**	**70.9**
			199.7	59.1	127.2	-1.6	158.5	-3.0	9.8	118.2	209.1	37.7	1.9	7.0	-1.3			
			67	154	559	320	398	183	97	574	357	72	73	207	168			
4	Giannis Antetokounmpo	PF	36.7	-57.9	685.1	20.0	388.5	103.4	131.6	713.1	289.8	62.0	115.7	-17.4	11.2	0.348	**190.9**	**66.4**
			12.8	-20.2	238.4	7.0	135.2	36.0	45.8	248.2	100.9	21.6	40.3	-6.1	3.9			
			102	156	337	284	169	12	25	287	622	99	19	156	166			
5	Chris Paul	PG	133.4	43.8	294.7	-4.1	163.3	-2.4	18.6	236.9	790.9	106.9	9.8	11.4	-4.1	0.139	**138.4**	**19.2**
			18.5	6.1	41.0	-0.6	22.7	-0.3	2.6	32.9	109.9	14.9	1.4	1.6	-0.6			

Top Five NBA Regular Season MVP Vote Getters | 2021-22

			97	191	667	356	379	89	206	813	584	109	63	281	191			
1	Nikola Jokić	C	42.1	-102.1	716.5	-22.8	362.4	11.5	405.0	1113.2	520.6	92.9	103.3	-14.8	36.4	0.875	**251.1**	**219.7**
			36.8	-89.4	626.9	-20.0	317.1	10.1	354.3	974.0	455.6	81.3	90.4	-13.0	31.9			
			93	158	573	510	654	149	146	650	284	77	99	214	181			
2	Joel Embiid	C	40.4	-84.5	615.5	-32.7	625.3	19.3	287.0	890.0	253.2	65.6	162.3	-11.3	34.5	0.706	**220.4**	**155.6**
			28.5	-59.6	434.5	-23.1	441.5	13.6	202.6	628.3	178.7	46.3	114.6	-8.0	24.4			
			71	171	618	385	553	213	134	644	388	72	91	219	212			
3	Giannis Antetokounmpo	PF	38.9	-64.3	757.4	24.0	539.8	120.3	181.8	800.1	315.0	62.0	144.2	-18.4	14.1	0.595	**224.2**	**133.4**
			23.1	-38.3	450.7	14.3	321.2	71.6	108.2	476.0	187.4	36.9	85.8	-11.0	8.4			
			183	295	479	464	315	48	45	297	329	77	26	162	180			
4	Devin Booker	SG	239.9	94.1	430.4	-44.0	371.7	-6.6	28.5	211.2	322.9	80.6	16.8	13.5	9.3	0.216	**136.0**	**29.4**
			51.8	20.3	93.0	-9.5	80.3	-1.4	6.2	45.6	69.7	17.4	3.6	2.9	2.0			
			201	368	440	394	364	125	56	537	568	75	36	292	145			
5	Luka Dončić	PG	262.9	103.4	384.8	-5.7	351.8	-25.4	41.7	443.3	722.3	81.0	18.6	21.2	-3.5	0.146	**184.3**	**26.9**
			38.4	15.1	56.2	-0.8	51.4	-3.7	6.1	64.7	105.5	11.8	2.7	3.1	-0.5			

Top Five NBA Regular Season MVP Vote Getters | 2022-23

			66	134	662	466	661	110	113	557	274	66	112	226	205			
1	Joel Embiid	C	28.6	-71.7	711.1	-29.9	632.0	14.3	222.1	762.7	244.3	56.3	183.6	-11.9	39.1	0.915	**213.9**	**195.7**
			26.2	-65.6	650.7	-27.4	578.3	13.0	203.3	697.8	223.5	51.5	168.0	-10.9	35.8			
			57	92	589	284	341	74	167	650	678	87	47	247	174			
2	Nikola Jokić	C	24.7	-49.2	632.7	-18.2	326.0	9.6	328.3	890.0	604.4	74.2	77.1	-13.1	33.2	0.674	**224.6**	**151.4**
			16.7	-33.2	426.4	-12.3	219.7	6.5	221.3	599.9	407.4	50.0	51.9	-8.8	22.4			
			47	124	660	447	498	274	137	605	359	52	51	246	197			
3	Giannis Antetokounmpo	PF	25.7	-46.7	808.9	27.9	486.1	154.7	185.9	751.6	291.5	44.7	80.8	-20.7	13.1	0.606	**215.7**	**130.7**
			15.6	-28.3	490.2	16.9	294.6	93.8	112.7	455.5	176.6	27.1	49.0	-12.5	7.9			
			240	446	487	386	531	91	78	571	342	78	51	213	160			
4	Jayson Tatum	SF	252.2	9.0	499.3	20.7	537.7	-8.3	56.7	582.8	279.4	81.0	55.7	-12.5	-22.7	0.280	**179.3**	**50.2**
			70.6	2.5	139.8	5.8	150.6	-2.3	15.9	163.2	78.2	22.7	15.6	-3.5	-6.3			
			58	110	646	567	669	70	59	270	371	112	65	192	192			
5	Shai Gilgeous-Alexander	PG	75.9	30.9	564.9	-8.2	646.6	-14.2	43.9	222.9	471.8	120.9	33.6	14.0	-4.7	0.046	**169.1**	**7.8**
			3.5	1.4	26.0	-0.4	29.7	-0.7	2.0	10.3	21.7	5.6	1.5	0.6	-0.2			

Average	**140**	**242**	**524**	**429**	**457**	**105**	**100**	**464**	**459**	**104**	**54**	**243**	**168**