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Playing With Analytics: How Basketball Teams Should Use Data When Making Decisions

Thomas Pollard

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Thomas G. Pollard
Iowa State University
2167 Union Dr.
Ames, IA 50011-1350
Tel: (515) 294-8300
email: tpollard@iastate.edu

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ABSTRACT

Modern technology has allowed for the collection of massive amounts of data. All kinds of industries have seen great improvements in efficiency and production through analyzing this information. Basketball teams are no different. Careful analysis and proper integration with the art of coaching can allow teams to make better decisions and be more successful. Teams can reap the benefits of adopting an analytical approach in areas such as strategy, player acquisition, and scouting. Computers should not and will not ever replace the knowledge of coaches and NBA front office members. Utilizing data analytics can provide basketball teams greater insight to make more informed decisions, but coaches and general managers should remember that it is just one piece of the puzzle.

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In the rapidly changing and uber-competitive world of sports, everyone is searching for the slightest advantage. Baseball was the first sport to see data change the game. Billy Beane and the Oakland Athletics adopted the use of statistics to help drive better decision making and viewed baseball through the lens of buying runs. The approach was coined "Moneyball". As technology improvements have allowed more data to be captured, other sports have followed suit. Baseball is unique in that every play has a beginning and end. Football is the same way. Sports like basketball and soccer are free-flowing and would appear to be much trickier to analyze (Foster et al., 2021; Gerrard, 2007). The research question defining the purpose of this paper is "what role should analytics play in decision making for basketball teams"?

Gerrard (2007) asks the very question of whether "Moneyball" can be applied to basketball and identified three types of barriers: technological, conceptual, and cultural. The cultural barrier will always be present, but the last five to ten years has changed a lot. The accessibility to analytics has changed the way fans view and understand players. Being a former player is no longer a so-called prerequisite to working in basketball. As the younger generation ages and moves into leadership positions, it would seem that this barrier will become less and less significant.

The technological barrier is not the same as it once was in the NBA. Cameras are installed in every arena to track movement patterns of all 10 players and the ball. Most teams have an in-house analytics department to provide them with valuable insight. However, it very much still exists in college basketball. With much more limited resources and no player tracking data, there is less to be studied in the college game. It only seems like a matter of time though before player tracking data is brought to college. The conceptual barrier tends to overlap with the technological one a bit. While Gerrard (2007) showed it is possible to incorporate team's concepts into analytical framework, it is not always easy. With the proper staff this barrier can be overcome through careful interpretation of metrics and utilizing best practices.

There is too much power in analytics for teams to ignore it. Just like football coaches must decide whether they are going to punt or go for it on fourth down, basketball coaches have to make tricky in-game decisions too. Adopting an analytical approach could allow teams to better prepare for handling decision making in crunch times of games (Bar-Eli et al., 2006; D'Amour et al., 2015; Maymin et al., 2011; Walco, 2018). Player tracking data has also changed the way offense and defense are approached in the modern game (Alferink et al., 2009; Goldsberry, 2019; Lamas et al., 2015; Miller & Bornn, 2017; Skinner, 2010; Skinner & Goldman, 2015).

Offenses emphasize efficiency. This can be seen in greater floor spacing, more three point attempts, and less post-ups (Goldsberry, 2019; Lucey et al., 2014). Defensively, teams using data are more prepared for their opponents' tendencies and abilities. Both of these used to be tougher to identify in film but can now be tracked and quantified (Bartholomew & Collier, 2011; Cervone, D'Amour, et al., 2016; Lamas et al., 2015; Le et al., 2017; Sicilia et al., 2019). This has allowed teams to make proper adjustments and force their opponent into less desirable outcomes (Cervone, Bornn, et al., 2016; Cervone et al., 2014; Hofler & Payne, 2006; Lucey et al., 2014).

With better statistical measures of performance, teams can more accurately measure player skill and impact (Bornn & Daly-Grafstein, 2019; Daly-Grafstein & Bornn, 2019; Fearnhead & Taylor, 2011; Malarranha et al., 2013). Teams can use this data to make more informed roster construction decisions. Coaches can use these tools to become better talent evaluators and allocate financial resources more efficiently to fill out their teams (Cervone et al., 2014; D'Amour et al., 2015; Deshpande & Jensen, 2016; Gerrard, 2007). Analytics can even give teams better insight into how a player may progress through their career so that they can better project a player's potential (Berri et al., 2011; Drakos et al., 2010; Silver, 2015).

IN-GAME STRATEGY

The typical sports fan might think the difference between a win or a loss in a basketball game could be as little as a bad bounce or a lucky shot. While the final plays of a close game are critical to the outcome of a game, there is a lot more that goes into preparing a team for those moments than meets the eye. Coaching staffs spend hours preparing for upcoming opponents and installing set plays to be run at critical moments or after time-outs (ATO's). Players must earn their coach's trust through hustling in practice and executing properly in drills. Data analytics can help coaches process all this information better so they can make smarter decisions, run a more efficient offense, and get their team to play stingier defense.

Decision Making

Due to the unpredictability of basketball games, coaches often find themselves having to make a quick, gut decision on something they are not completely prepared for. Fans and media love to praise or critique coaches on their strategy based on the outcome of the game. Whether a team won or lost is not always a fair way to evaluate a coach's decisions because that ultimately comes down to the ability and execution of the players on the court. A coach could draw up a perfect play that gets their best player a wide-open look, but the player could miss the shot resulting in a loss. However, some of the greatest debates surrounding in-game decision making can be answered by looking at historical data.

One of these debates revolves around a last-second shot. With the game on the line and a chance for their team to attempt a game-winning shot, should the coach give the ball to their best shooter or the guy with a "hot hand"? Bar-Eli et al. (2006) attempted to determine the validity of the "hot hand" theory by investigating research done on the topic. A "hot hand" can be best described by the belief when a player has made a few shots in a row, they are more likely to make their next shot than usual. Most of the research done on basketball shooting streaks failed to support any relationship between the outcome of a player's previous and future shot attempts. Given this information, coaches can keep all their options open and be less predictable with where the ball is going for the final shot.

Forcing the ball to one player or isolating your best player is not necessarily the best move. Ball movement has been shown to result in more open and efficient looks (D'Amour et al., 2015; Lucey et al., 2014). Skinner (2010) likened basketball shot selection to a traffic congestion problem showing the unpredictability associated with not always chasing the most efficient shot is more efficient in the long run (Steinberg & Zangwill, 1983). Instead of focusing on the debate over who should take the last shot, coaches should focus on how to get the last shot. This is where the human element takes over as the professional expertise of a coach trumps all.

Another issue coaches are put under the microscope on is their handling of players in foul trouble. Coaches are often put in a tricky spot when one of their players picks up a couple early fouls. It takes five personal fouls in college and six in the NBA for a player to be disqualified from a game. Should they put the player on the bench to protect them from picking up another costly foul or trust them to play through it? Just like the public, the research cannot seem to find a consensus. Walco (2018) found that saving a player in foul trouble for the final minutes of the game is not worth the lost production of benching that player for stretches during the game. Teams play better when a key player is on the court and in foul trouble rather than sitting on the bench while a sub plays.

On the other hand, teams perform worse after a player fouls out (Gomez et al., 2016). This effect is expected as it makes logical sense for a team to play worse without one of their key players. Coaches must find the right balance between protecting a player in foul trouble and reaping the benefits of said player being on the court. Maymin et al. (2011) analyzed data from NBA games in 2006-2009 and found the optimal time to bench a player was when a player had one more foul than the quarter number. For example, if a player had two fouls in the first quarter they should be benched until the second. If they pick up a third foul in the second quarter, they should be benched until the 3rd and so on. This does not directly translate to college since games are broken up into two halves instead of four quarters and the foul limit is one less. Regardless, none of the evidence presented can definitively provide an answer for every situation. Coaches should use their best judgement along with how much they trust or need a player in the game when deciding if the player should be benched.

Another in-game decision where coaches face heavy criticism, no matter what they do, is with regards to the rotation. Whether it is an upset parent thinking their kid deserves more playing time or a know-it-all fan convinced a certain lineup is the best, coaches will never please everyone with their substitution patterns. Data can be used to help coaches understand their best lineups. Player tracking data can be used to understand each player's skillset and estimate the performance of potential lineups (Skinner & Guy, 2015). Coaches do this as well. It would be interesting to see how the model used in this study would compare with the assessment of a team's coaches. Coaches spend every day with their players and nothing can replicate the coach-athlete relationship. While player tracking data can be used to assess a player's skills, it may be more useful for understanding an opponent than one's own team.

Some of the most important factors in team performance are limiting turnovers and shot-making abilities (Hofler & Payne, 2006; Sampaio et al., 2010). Turnovers drive coaches crazy. Not only is it a waste of a possession, but it often leads to an easy basket for the other team. This only validates the frustration of coaches watching turnovers on film. Lineups can also be viewed as strategic networks and the following variables were found to be significant in the functionality of lineups: entropy, centrality, and clustering (Fewell et al., 2012). In basketball terms, these variables roughly translate to ball movement, leadership, and spacing. Every team has an optimal system given their unique personnel. With five players on the court at once, their fit together is just as important as individual skillsets (Skinner & Goldman, 2015). Coaches can use these tools as another piece of information in determining the most efficient combinations and pair them together to create substitution patterns.

Offensive Philosophy

No offensive strategy is inherently better than another. If that was the case, everyone would run the same offense. One of the toughest jobs coaches have every offseason is examining their lineup and determining what offensive system puts those players in the best position possible to win games. Offenses have evolved through the years, but today you will see teams running different variations from five-out, four-out, the triangle, swing, Princeton, etc. Teams even play positionless basketball, as player roles are no longer defined by the position they play (Bianchi et al., 2017). Each type of offense has different spacing, puts the ball in the hands of different players, and creates a different distribution of shots (Fewell et al., 2012). It is up to the coach to determine the optimal strategy for their team and analytics can help do that (Skinner, 2010).

Bayesian methods can be used to study offensive and defensive interactions and predict outcomes (Lamas et al., 2015). The probability of different outcomes can be calculated based on how the defense guards what the offense runs. The different outcomes of a “space creation dynamic” (SCD) are a free shot, contested shot, foul, turnover, reset, and new SCD. For example, the most common outcome when the defense switches a pick and roll was a reset by the offense 31.5% of the time. Of the five SCDs, a one-on-one play in the post resulted in a foul the least and a one-on-one play on the perimeter resulted in a contested shot the most. Coaches could use this type of information to figure out how a defense might guard their team based on each player’s skills. Additionally, a coach can quantify the expected probability of each outcome based on the frequency of SCDs and how the defense chooses to defend.

There is plenty of room to grow in studying offensive structure using player tracking data. Possessions can be mapped and compared to other similar sets using kNN (Miller & Bornn, 2017). Coaches could potentially pull up clips of offensive possessions that looked like one their team ran to identify teaching points and install counters. Watching other teams successfully run certain plays would help improve their execution of the same play. Both NBA and college teams play the same opponents multiple times during a season and teams can become quite familiar with one another. Installing slight variations of the play could catch these defenses off-guard because they would be expecting one thing and seeing another (Lucey et al., 2014; Skinner & Guy, 2015).

Offenses only get so many possessions each game, so it is important to be efficient with them. Shot selection has become one of the biggest talking points in basketball, as the NBA game has revolutionized toward taking the most efficient shots (Goldsberry, 2019; Malarranha et al., 2013). Over recent years, emphasis has been put on taking threes and layups because they result in the highest points per shot. Teams have prioritized spacing the floor to open driving lanes to the hoop, thus making it tougher for defenders to help. If a defender helps, they likely have a longer way to go to recover on their man and are prone to giving up open threes. Due to how much more likely an open shot is to go in versus a contested shot, an offense's job should be to work for an open look every time (Lucey et al., 2014).

Before player tracking data, measuring shot selection was largely subjective. Teams could look at how many shots players were taking, what types they were, and roughly how open the player was. Methods to analyze this data leave much to be desired (Alferink et al., 2009; Skinner, 2010). Basketball analytics are only as powerful as the changes they result in. If conclusions do not result in implementable actions, then they are useless. Player tracking data has provided a more useful way of evaluating shot selection and that is due to the variable "expected possession value" or EPV (Cervone et al., 2014; Cervone, D'Amour, et al., 2016; Lucey et al., 2014; Sicilia et al., 2019; Skinner & Goldman, 2015). EPV considers each player's positioning and abilities to calculate the average value of every decision in a possession. Ideally, teams would shoot the ball when the EPV was highest in every possession. This is near-impossible to know in real-time, but it is a useful tool for analyzing games after they have been played.

Not only can EPV help coaches understand where and when shots should have been taken, but it also allows them to evaluate each player on their ability to make correct decisions (Cervone et al., 2014; Cervone, D'Amour, et al., 2016; Sicilia et al., 2019). Possessions can be reproduced as a still-image showing players who they should have passed the ball to in that specific situation. If a coach is struggling to get a player to share the ball with their teammates, the coach can use this graphic as evidence to why they should pass the ball more. Coaches can quantify each decision in a play to help their team understand how many more expected points would have resulted out of different choices. To build on this further, coaches can understand how much EPV their team left on the court each game. It is up to the coaches to put players in a position where the EPV is highest, but it ultimately comes down to the players to make the right read and knock down shots. This would be very helpful when a team is struggling and needs to look itself in the mirror to self-scout and figure out what needs to change to get back in the win column. Sometimes they may even see that they are doing everything right and will notice a difference once shots start to fall.

Maximizing EPV is necessary for teams to play their best, most efficient games (Cervone et al., 2014; Sicilia et al., 2019). Offensively, no matter how well a team passes and takes care of the ball, they need to make shots. Shot-making ability can be presented simply as field goal percentage or in more advanced ways like effective field-goal percentage. Daly-Grafstein and Bornn (2019) present an improved way to estimate a player's field goal percentage by using the Rao-Blackwell Theorem. The Rao-Blackwell field goal percentage can help coaches better estimate future performance of shooters and could use this data when considering playing time and player roles. Coaches are always looking for every advantage they can and knowing a certain player will be a 40% three-point shooter while another will only be a 36% three-point shooter could change how many minutes they get.

Efficiency is about more than just shooting. Hofler and Payne (2006) found that higher quality coaching was significant in win efficiency, a measure of how closely a team played up to their respective potential. Just because the most efficient shots in basketball are threes and layups, does not mean they are the most efficient shots to take every possession (Goldsberry, 2019). Not every player can shoot threes or finish at the rim. Coaches are responsible for helping players understand their own strengths and weaknesses. If a player is most efficient at the right elbow, then teams should scheme to get that player the ball there (Cervone, Bornn, et al., 2016). Basketball courts can be viewed like real-estate. Location is one of the most important factors in determining value. A dominant big man is not valuable on the perimeter, just like a skilled shooter may not be valuable playing in the paint.

If a player cannot shoot but is a skilled rebounder, a coach needs to get the player to buy-in to putting his or her energy into rebounding. Players provide the most value when they put their energy into doing what they are best at. Fearnhead and Taylor (2011) estimated NBA player values on offense and defense, which helps show there is value in having players with different skills. While it is a great luxury for teams to put five players on the court that can shoot threes, it is not necessary to win (Cervone, Bornn, et al., 2016; Cervone, D'Amour, et al., 2016; Deshpande & Jensen, 2016; Fewell et al., 2012; Lucey et al., 2014; Skinner & Goldman, 2015). Deshpande and Jensen (2016) used a win-probability framework and linear regression model to estimate how much each player contributed to their team's success. Using win-probability in their calculations allowed for them to identify plays that were the most critical in determining the outcome of games. This study gives coaches better insight into how players are being used and their roles on their respective teams. Coaches have a good feel for how talented their players are, but methods like this outline ways to numerically evaluate each players actual production and impact on the court. Efficiency leads to wins, so efficient production is the goal (Hofler & Payne, 2006).

Defensive Philosophy

The use of analytics has changed the way teams view offense, but it has struggled to make an impact on the defensive side of the ball largely due to the difficulty of measuring defense (Bornn & Daly-Grafstein, 2019; Fearnhead & Taylor, 2011; A. Franks et al., 2015b; Le et al., 2017). Traditional stats like steals and blocks only capture so much and have been found to not be truly indicative of defensive abilities (A. Franks et al., 2015a). Bornn and Daly-Grafstein (2019) use player tracking data to better understand defense and why contesting shots results in a lower field goal percentage. Instead of evaluating shots on a make or miss basis, they are able to use shot trajectories as well as derived shot factors to measure shot-making probability. Taller defenders and the distance from the defender to the shooter both impact the trajectory of shots (Bornn & Daly-Grafstein, 2019; Lucey et al., 2014). Coaches can use this information to evaluate how their players affect shots and how often they do so while on the court.

Specifically looking at defensive positioning, defenders can be rated based on their ability to affect shot efficiency and frequency (A. Franks et al., 2015b). This is another piece of information that is missing from box scores. Some players are such strong defenders that opponents are not even able to get shots off. Lockdown defenders like this are a rare breed and their impact goes far beyond stats like steals, blocks, or their impact on shot trajectories. Keshri et al. (2019) shows how defensive assignments and events can be automatically labeled in NBA game film. This saves time and makes future analyses of defensive assignments more accurate and insightful.

Player tracking data helps manage the difficulty in measuring defense, but this data is not available at the college or high school level. College basketball teams must rely on less robust technology and even student-managers coding games by hand. However, this has not stopped teams from trying to find something to measure. Higher rates of contested passes has been shown to lower an opponent's field goal percentage (Bartholomew & Collier, 2011). While very simple, defensive points of focus backed by data like this can be very helpful for coaching staffs looking for every advantage they can find.

Coaches have a few different options when it comes to deciding how they want to structure their defense. The main things coaches must figure out is how they want their team to defend ball screens, defend the post, and help. A useful way for coaches to understand ball-screen defense is through spatiotemporal data (Franks et al., 2015b). A concept like ball-screens can be broken down and filtered by the players involved, location on the court, time left on shot clock, etc. Coaches can use this data to help players become better ball-screen defenders and develop a plan for ball-screen defense. Coaches do not need this data to do any of this as they can see lots of this themselves but having the data to confirm what they see provides value and may help them do this job quicker.

Just like an offense may prioritize getting players the ball in certain areas on the court, defenses can prioritize keeping offenses out of certain zones (Cervone, Bornn, et al., 2016; A. Franks et al., 2015b). In addition, teams can locate spaces of the floor where certain players are not a threat. Whether a team is preparing for certain opponents or developing a long-term defensive strategy, spatial data can be beneficial. For example, analytics could help players know why their coach is telling them to force an opposing player to shoot threes. The players can look at the math behind the decision and see why they should remain consistent to this approach even if the player they are guarding gets lucky and makes two in a row. Players and coaches tend to have recency bias and want to overreact to a few minutes of gameplay, but accurate data over a longer period is more reliable. Player tendencies can be identified with the belief that they will regress to the mean (A. Franks et al., 2015b).

While analytics provide great information leading up to games, coaches must make effective adjustments during the game based on what their opponent is doing. This is an area where analytics lacks in its ability to make a difference. However, analytics can help coaches prepare for adjustments they may need to make in-game. For example, if a team is struggling to score on offense, it may make sense to start playing more aggressive defense (Skinner & Goldman, 2015). Instead of allowing the opponent to run meaningless actions beyond the arc, a team could ramp up the pressure and get in passing lanes (Bartholomew & Collier, 2011). Teams could also elect to help off certain players and put more attention on the opponent's best players. Different strategies like this could spark some momentum for a coach's team. If the offense crumbles at the pressure and turns the ball over or they could result in easy baskets in transition. Coaches already make these types of adjustments based on their own expertise and intuition, so analytics play a very small role in a coach's decision-making process.

The easiest time for coaches to use data to make adjustments during a game is at halftime. Teams can sit down and talk without crowd noise playing a factor and coaches can look at analytical recaps of the first half. Player tracking data can show how an opponent is getting their points, but coaches have a good feel for this by watching the game too (Hofler & Payne, 2006; Lamas et al., 2015; Sicilia et al., 2019). Even if a coach just checks the stat sheet for 20 seconds before preparing a message to their team for the second half, it may be the difference between missing a key detail or not. The real focus for a coach at halftime is getting their players in the right state of mind to be successful in the second half. Teams should focus on having the right matchups and doing what they can to keep their players guarding those players (A. Franks et al., 2015a). Analytics should never be a priority but should play a role in how part of those adjustments are made.

Halftime also provides a time for coaches to teach. Teams could use deep imitation learning to show players where they should have rotated (Le et al., 2017). This can be done by praising players for making the correct decision on the angle they took when closing out on a player or correcting bad decisions. It is much easier to do this with the film to back it up. Deep imitation learning would help coaching staffs identify what plays need to be addressed quicker so that they can get these video clips ready to be shown to the players. Adjustments will only work if they are implemented successfully. The less coaches have to worry about how they are going to teach their players, the more they can focus on what they are teaching them, and this technology will help with that.

Roster Construction

Coaching can only take a team so far. Ultimately, the talent level of a team determines the heights the team is capable of reaching in a given season. In college, the responsibility of acquiring talent falls in the hands of the coaching staff as recruiting is a large part of their job. In the NBA, general managers and front office personnel are assigned the duty of signing players. Analytics can benefit teams at both levels when it comes to building a roster, but the NBA has more uses for it than college teams due to limited data on high school players.

Player Acquisition

Basketball teams acquire players through a variety of ways. College teams can recruit high school players or transfers from another college through the transfer portal. At the professional level, it is through the NBA draft, free agency, or trades. Every summer the NBA has a two-round draft where every team has one pick per round assuming they have not previously traded the pick. NBA scouts, media personalities, and fans love to speculate over what draft-eligible players have skills that translate the best to the pros. It is not easy to predict how good players will be, but attempts are made each year to predict future player performance (Berri et al., 2011; Silver, 2015). Teams must decide how they want to draft. Do they want to take the best player available? Will they draft the player with the highest potential? Will they draft off positional need?

If a team values potential over production, age becomes an important factor. Players have been found to improve through the age of 27 before beginning to see a decline in performance (Silver, 2015). Players who rely more heavily on skill versus athleticism will likely see performance decline at a slower rate than a player whose best attribute is athleticism. NBA teams probably have their own models to predict player performance but keep that information confidential. A recommendation I would have for teams is to identify the specific traits that translate most to success at the next level and then target that in player acquisition. For college basketball teams scouting high schoolers, they may not have advanced enough data to study usage rate or efficiency stats. They may have to rely more on the eye test and subjective measures of how much better players can get at shooting, finishing, or playmaking. Since much more data is tracked on college players, NBA teams can study more advanced stats to find translatable numbers.

One draft or recruiting strategy teams will take is picking the best available player. Teams will focus on accumulating talent and worry about their fit on the court later. There are many different ways to define the "best" player (Berri, 1999; Deshpande & Jensen, 2016; Fearnhead & Taylor, 2011). A great example of this is the NBA MVP race each year. The media and fans argue all the time over the definition of "valuable" and what that means. Berri (1999) proposes a model to relate a player's statistical production to team wins. NBA teams and college teams use this approach when scouting players. The best players do not always put up the biggest numbers (Deshpande & Jensen, 2016). Identifying talent that will be able to produce at the next level is more important. Advanced analytics can help make this tricky job a little easier.

Teams also consider character issues, personalities, and injury history. One of the biggest parts of dependability is availability. If a player is hurt that is a waste of money for the team. Team doctors can examine an athlete's medical records and identify players that may be higher risk for certain injuries (Deshpande & Jensen, 2016). Drakos et al. (2010) found that athlete demographics like experience, age, height, and weight had no relationship with injury rate. This means the most important piece of information regarding a player's future health for teams to consider when drafting players is their injury history (DiFiori et al., 2018). Training volume has also been shown to be a risk factor for injuries as the harder players work, the more likely they are to get injured. Teams need to be careful when ramping up a player's workload and need to consider their previous training.

Knee injuries are the most serious, as they result in the most missed time per injury. Ankle injuries are the most common, making up 14.7% of all injuries in the NBA (Drakos et al., 2010). The same is observed in women's basketball with 47.8% of players at the WNBA combine having had a previous ankle sprain (McCarthy et al., 2013). Colleges may want to be careful recruiting players who have dealt with a reoccurring injury because it is likely to continue plaguing them in college.

Identifying Needs

If a team is recruiting or drafting off need, they first need to evaluate their own team to decide what it is their team is missing. This can be done by simply looking at the depth chart and identifying which positions lack depth. It can also be done through understanding player skills (Bianchi et al., 2017; Skinner & Guy, 2015). The term "positionless" has been a buzzword in basketball circles lately and this is largely due to schemes emerging that do not define set positions. Defenses have started switching screens more often, making players that can guard multiple positions highly coveted. Skinner and Guy (2015) propose a network-based strategy that could allow coaches to better evaluate personnel and potential lineups. Not every point guard plays the same way, just like not every seven-foot center is comfortable posting up with their back to the basket. Before committing to signing a player, coaches and management should use models like this to predict their fit with the current team and measure its effectiveness.

Coaches also need to figure out how a player fits their system and culture. Every team could use another "team-first" guy because there are only so many minutes to go around. Not every player can bring the ball up or lead their team in scoring. Players who figure out how to get minutes on the court are usually doing all the little things right and make their teammates better. In recruiting, no high school coach is going to tell colleges that their player is selfish or lacks a strong work ethic. These are things that a coach must pick up through the recruiting process by talking with the athlete. Relationship building is vital to a team's success on the recruiting trail and statistics will never be able to replace that.

In a general sense, advanced statistics can help coaches shape their ideal team or philosophy (Skinner, 2010; Skinner & Goldman, 2015). Coaches understand that no player or system is perfect, and they have to be willing to adapt. An NBA team may realize that their preferred free-agent target will not consider them due to the city they are located in or that player's ties to another team. College teams often recruit players from geographic regions close to them because the prospect is likely more familiar with their program, and it is easier for their family to travel and watch their games. It is also easier for the college coaches to travel and scout these prospects.

Coaches should assess the available talent, specifically the talent they can reasonably acquire, and use that in determining how they are going to be successful (Skinner & Goldman, 2015). If a team lacks mid-range scoring ability and a tough, hard-working, but inefficient player that can create their own mid-range shot wants to commit, the coach is likely better off taking that player instead of risking losing them by chasing others. Even if the coach does not prefer their team takes mid-range shots, living with a few a game by this player may be the best thing for the team since the player offers so many other benefits to the program. It is hard to quantify and measure this, but, if possible, I believe the numbers would support coaches making decisions like this. I would argue that all coaches, even those who are anti-analytics, are probably using statistical theories without realizing it.

Positional Makeup

Bianchi et al. (2017) attempts to create new labels for players using "fuzzy clustering and self-organizing maps (SOM)". Instead of defining the five positions as point guard, shooting guard, small forward, power forward, and center, players are one of the following: all-around all-star, scoring backcourt, scoring rebounder, paint protector, or role player. Rather than placing players in a certain position based on their other four teammates on the court, this method labels players based on their skillsets. These results are more effective and informative when it comes to understanding a player's strengths and weaknesses.

However, this methodology struggles to evaluate bench players on limited minutes. The role player bucket seems to capture too many different types of players. Teams need effective role players. It may be easier to get a bench player to buy-in to their role when it is clearly defined. Only five guys can play at a time, so coaches are responsible for keeping bench players excited and ready for their opportunities. When put in the game, that player does not need to try and play like the starter. Instead, that play should focus on their own skillsets. These skills can be better captured through practice time and drills rather than any statistical analysis from in-game box scores. This is an area where coaches should trust their own scouting abilities and focus on the human side of the game rather than the numbers. The best way to determine if a potential bench player fits a team need is through conversations and film study.

One way front offices and coaches can evaluate other players, assuming they have a large enough sample size, is by studying how they perform in certain actions (A. Franks et al., 2015b; Sicilia et al., 2019; Skinner & Goldman, 2015). Franks et al. (2015) shows how player tracking data can be used to understand who a player guarded and for how long during a possession. Additionally, this information can be used to measure a player's efficiency and effectiveness in defending certain actions. Even if a player only plays for ten minutes a game, coaches can have a good feel for how well that player handles certain scenarios both offensively and defensively. If a player struggles to guard in space and tends to get called for fouls when the opposing player drives past them, a coach may not want to add them to a lineup that already struggles to play defense. If a player shows a knack for distributing the ball to teammates, they may be a great fit on a team with a point guard who prefers to score. The positions each player is listed on the depth chart is less meaningful than the roles they fill on the court. It is a bigger problem than just the point guard if a team is struggling to share the ball or create open looks for one another. Even a great point guard may not be enough to mask a selfish team. Every team needs a certain amount of scoring, passing, rebounding, and defending on their roster. Each team likely values certain skillsets and attributes differently when it comes to player acquisition based on the skills and needs of their current team.

PLAYER EVALUATION

Utilizing data analytics in basketball allows for the creation of metrics that can be used to quantify and monitor performance over time. Some statistics are more advanced than others, but any that have enough meaning to be factored into decision-making can help teams be more successful or operate more efficiently. With small sample sizes, it can be easy to overreact to player performances. For example, a young freshman may get put in at the end of a blowout and hit back-to-back three pointers. Fans are likely to love the player and push for them to get more playing time, but the reality is that the player is not going to do that on a consistent basis. Structurally-sound statistics can help teams discern noise from baseline ability (Bornn & Daly-Grafstein, 2019; Brown & Sauer, 1993; Daly-Grafstein & Bornn, 2019). If an NBA player who is historically a good rebounder dramatically struggles to grab rebounds for a couple weeks, it may be a sign of bad luck rather than a decline in performance. Rather than benching the player or deciding not to re-sign them, teams can use historical data and advanced statistics to help shape their belief of a player's value both in the present and future.

Advanced Metrics

The first thing most people do after a game is check the box score. While informative, these stats can be misleading as they do not necessarily capture everything from a game (Bornn & Daly-Grafstein, 2019; Cervone et al., 2014; A. Franks et al., 2015a). Statistics derived from box score stats or captured from player tracking data can do a better job describing how a player or team performed (Deshpande & Jensen, 2016). Players may only take a few shots a game. There is a big difference in percentages if a player makes two out of five shots instead of three. On a box score, a player that went three for five would have shot 60% from the field while a player shooting two for five shot 40%. This information could be easily taken out of context to show that one player is much better than the other.

The difference in performance for this example was only one made shot. Over an entire season there is less concern for this type of error as the sample size will be larger, but it highlights how field goal percentage may not always properly measure shooting performance. As mentioned, Daly-Grafstein and Bornn (2019) have used the Rao-Blackwell theorem to develop a shooting statistic with less variance than field-goal percentage. Shot-making ability should encapsulate more than just the outcome, as every shot is different (Lucey et al., 2014). Multiple players are involved in shots: the shooter, closest defender, any help defenders, and even teammates. The goal of every possession is to get an open shot and teams can drill down into different metrics that help create open looks. Lucey et. al (2014) found a few different variables in the three seconds leading up to a shot to be significant in that shot being open. Those variables were the average distance moved by the defense, maximum distance moved by a defender, average velocity of a defender, average acceleration of the defense, number of dribbles taken, number of possessions taken, and number of defensive role-swaps.

A team struggling to create open looks may use this information to see how well they are forcing teams to switch and figure out ways to do a better job of that. This could also explain the recent trend of NBA teams valuing players that can defend multiple positions so highly (McMahan, 2018). The reason offenses run so many pick-and-rolls in today's game is because it causes one of two things. If the defense does not switch ball screens, and the screener successfully screens the defender, the offensive player with the ball should have open space to either shoot or drive. If the defense decides to switch the action, there is potential for a mismatch. Screeners are usually taller players so the player with the ball would then have a taller and presumably slower player guarding them. Additionally, the screener may now have a smaller player guarding them and can more easily post-up. Either way, the offense is in control of the situation and can attack the bigger mismatch.

Any time an offensive player receives the ball, they have a decision to make. Should they shoot, pass, or dribble? Statistics to measure decision-making can be derived from player tracking data (Cervone, D'Amour, et al., 2016; Cervone et al., 2014; Metulini et al., 2018; Sicilia et al., 2019). EPV has already been mentioned but it creates the opportunity for further analysis. Cervone et al. (2014) explains how EPV-added, EPVA, can be used to quantify offensive value. This statistic should be easier to compare between players across the league as it is not reliant on teammates' abilities. EPVA measures how much better or worse a player performs compared to the average player in that situation. It will always be difficult to compare a point guard on an awful team with a point guard on a great team and truly know how they would perform given the other's situation. Assists are very dependent on teammates' abilities to make shots and could be called an outcome-based stat, where EPVA is a process-based statistic. Thus, EPVA should create a level-playing field for comparing players from different teams.

Cervone et al. (2014) also details a metric called "Shot Satisfaction". This helps to account for whether or not players are shooting from spots on the court they are effective at as well as how well the defense had them covered when the shot was taken. Players are rewarded for dribbling to more dangerous spots on the court, making the correct pass, or taking the correct shot. EPV also allows for the measurement of selfishness. Does a player shoot the ball when the best play is to pass it? Coaches walk a fine line when telling their players they need to share the ball more with their teammates without taking their aggressiveness away from them. Quantifying selfishness would help coaches learn what players are the most egregious offenders of taking bad shots and how hard they need to be corrected. To calculate this metric, the EPV of making a pass at the point in time a player shoots the ball is subtracted from the EPV of taking the shot. Positive values correspond to unselfish play and negative values correspond to selfish play. Coaches can decide how much they want to utilize stats like this, but any time something like this can be quantified, it should only help players and coaches understand the topic better.

Box score statistics for defense are limited to steals and blocks, but advanced metrics derived from player tracking data can help teams better quantify defense (Deshpande & Jensen, 2016; A. Franks et al., 2015a, 2015b). The amount of attention players draw on offense, both on and off the ball, can be calculated and measured (A. Franks et al., 2015b). Attention is not inherently bad or good. Star players often command lots of attention because defenses are focused on stopping them. Teams should ideally give a certain amount of attention to players based on the amount of time they have the ball and the quality of their teammates. Teams can use this stat to compare their defensive strategy with other teams. For example, you often hear NBA teams talk about "building a wall" when guarding Giannis Antetokounmpo. In previous seasons, teams like the Celtics and Raptors have done a great job of slowing him down using this strategy. In the 2021 NBA Finals, the Phoenix Suns talked about building a wall but struggled to effectively build one. While they might think they were devoting lots of attention to Giannis, perhaps they could have used this attention stat to compare the attention they were giving him to the levels of teams who were able to slow him down.

In addition to attention, defensive entropy can be calculated (A. Franks et al., 2015b). Defensive entropy is a way of measuring the activity level of players on the defensive side of the ball. The more active a player is in helping on other players and switching, the higher their entropy will be. An entire team's entropy can be found by averaging all their players on the court. Defenses with a high entropy level play hard and are very active on that side of the ball.

Additionally, offenses that induce high amounts of defensive entropy are making the defense work harder than offenses inducing low amounts.

Franks et al. (2015a) mentions other ways that defensive performance can be measured and displayed. Both shot volume and shot disruption can be mapped on a shot chart. This allows coaches to quickly and easily decipher where their players are being scored on and how successful they are at reducing an opponent's effectiveness as the primary defender. The beauty of shot charts is that it displays the entire court and carries more information than a simple number.

Franks et al. (2015a) also attempts to create two stand-alone defensive measures that better assign defensive responsibility since the closest defender is not always most responsible for giving up the shot. If two defenders switch assignments right before the shot is taken, the blame could fall on the original defender. The defense may have only switched because the initial primary defender was out of position. Time-varying volume score measures the ratio of shot attempts a defender's matchup takes versus the expected number of attempts they should face. Players with a high score in this make it easier for their opponent to shoot. This same ratio can be calculated looking at points instead of shot attempts. Coaches can use this stat to identify the players on their team doing a good job of closing out and affecting the opponent's shot. They can also be used to coach up poor defenders and recognize players for improving in these areas throughout a season.

With any metric, especially those that are derived, coaches and statisticians need to be sure it is reliable and has value. There are three important questions that must be asked of any metric (A. M. Franks et al., 2016). First, how well does the metric discriminate between players? If every player had the same or very similar values, then the metric is not helpful. Secondly, how stable is the metric over time? If a player grades out very favorably by a certain metric one season, how confident can we be that the player will continue to grade out the same way moving forward? Finally, how independent is this metric from others? Is it telling us information we did not already know? A. M. Franks et al. (2016) presents how these three factors can be measured on any metric. Interestingly enough, when testing was done on a slew of in-game box score stats, three-point percentage was one of the least stable and least discriminatory. This would support the argument that shooting ability is better measured through shot trajectory data and could encourage teams to rely more on the eye-test when scouting shooters (Bornn & Daly-Grafstein, 2019).

Estimating Individual Impact

Scoring points, grabbing rebounds, and playing good defense are all valuable. But how valuable? Some of the advanced metrics mentioned so far try to quantify individual performances so that coaches and front offices can better understand why their team is winning or losing. "Glue guys" are often credited for helping their team win in ways that are not measured with stats. Besides statistics, lots of factors play a role in winning: team chemistry, spacing, anticipation, hustle plays, confidence, morale, in-game adjustments, and much more. Most of this will never be quantifiable, but statisticians have worked to quantify as much as they can.

Deshpande and Jensen (2016) created Impact Score using a win-probability framework to measure each player's individual impact to their team's chances of winning. Impact Score can also be calculated over an entire team's lineup and provides the ability for coaches to estimate a potential lineup's effectiveness. This comes in handy when preparing to trade for a player because a team could look at how the Impact Score of their different lineups would change.

Fearnhead and Taylor (2011) also provide framework for computing player ability, a metric that attempts to combine all areas of the game into one.

Teams can also use EPV and EPVA to predict how losing a player would change their team's performance (Cervone, D'Amour, et al., 2016; Cervone et al., 2014; Sicilia et al., 2019). Instead of using the average player as a baseline, a specific player could be used. This would allow front offices to compare one of their players to a free agent or potential trade target. Teams could potentially save money by finding players with a similar EPV but signing the cheaper option or building trade packages with this concept in mind. Comparing players with each other using stats like EPV could also help determine appropriate salaries for free agents. Ultimately the market determines player values, but teams could use data to create price ceilings for each player before entering negotiations.

Scouting Reports

Before every game, coaching staffs develop in-depth scouting reports of their opponent. This usually involves watching significant tape of the team and taking notes on different offensive actions to expect and any flaws that could be exploited. They will clip pieces of games to show to their team and share key statistics or tendencies of their matchups. Teams usually do not have long layovers between games and must prepare rather quickly. The quicker they can gain an understanding of their opponent the better. Automation can change the way teams prepare for opponents so that coaches can focus on preparing their team instead of repeating any monotonous tasks for every opponent.

Teams can use analytics to identify their best chance at beating a certain opponent. Any kind of machine learning algorithm could be used to test different approaches and the likelihood of them resulting in a win (Cao, 2012). When planning for an opponent, it is important to understand how they are going to try and score. Conceptually this is most commonly done through film study, but can also be done utilizing shot charts and automatic event detection (Cervone, Bornn, et al., 2016; Foster et al., 2021; Keshri et al., 2019). Historical data can also show how a superior team may struggle with certain types of matchups (Dutta et al., 2017). Given this information, teams could choose to alter their rotation or typical strategy to give themselves the best chance of winning.

IMPLEMENTATION

While all these tools and statistics are great, they are of no value if coaches decide not to use them. It is important to emphasize that these tools should never replace what a coach does. Computers will never be able to breakdown game film better than a coach can. Coaching will always be a blend of art and science that computers cannot reproduce. The purpose of analytics should be to help coaches capture data quicker and turn it into valuable insight for them to use. To overcome the stigma analytics may carry in some coaching staffs, there are three strategies that can help successfully integrate analytics into any organization (Shields, 2018).

The first key Shields (2018) mentions is to practice collaborative analytics. Coaches should work to blend components of analytics into their practices and gameplans. Shot-tracking data gives teams the ability to better measure a player's shooting abilities and identify teaching points for player development (Alferink et al., 2009; Lucey et al., 2014; Sicilia et al., 2019). Coaches may find it easier to discourage players from taking certain shots when they can show the player the numbers behind the decision. Players and coaches are already flooded with so much data, but staffs that can figure out a way to decipher meaning from the data are at a huge advantage.

Statistics can be hard to understand if the person explaining it to a coach talks too in-depth. To get people to buy-in to something they do not know anything about, one needs to make it easy for them to understand (Shields, 2018). A head coach is not concerned about the statistical reasoning behind proving some variable is significant. Instead, coaches only want to know what they need to know. Statistical tools that focus on specific concepts the coach cares about will be received much better than those that are not. For example, coaches do not care what the league average tells them they should do in each situation. Analytical framework should be built around a team's strategy, using their lingo, and focused on their specific personnel to gain the most value (Gerrard, 2007).

Lastly, teams that want to incorporate more analytics in their program should deploy accessible technology (Shields, 2018). There is no point in gathering lots of data if it cannot be easily accessed. In fact, any data captured that is not used could be considered a waste. If a team does not care about aggressively playing in passing lanes then it is not worth it to track contested passes (Bartholomew & Collier, 2011). Coaches are already overworked as-is, so resources should be put toward saving time and helping coaches operate as efficiently as possible. Coaches should want to take advantage of any insight analytics offer. If not, their staffs should make best use of their time by focusing on the actual coaching.

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