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The Role of Analytics in Assessing Playing Talent

Dr Bill Gerrard

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Abstract

This chapter considers the role that data analysis should play in decisions requiring an assessment of players whether it be young players in a youth development programme or established first-team regulars. *Moneyball* has highlighted the possibilities for analytics as a competitive strategy particularly for small-markets teams with relatively limited resources. This chapter will go beyond *Moneyball* to consider the problems of constructing player rating systems in the invasion-territorial team sports in which player performance is multi-dimensional. Drawing on decision theory and cognitive psychology, it is argued that the role of statistical analysis is secondary to the expert identification of the characteristics of optimal player performance. It is concluded that effective analytics in sport must always be coach-led.

Keywords

Analytics; *Moneyball*; invasion-territorial team sports; player rating systems; expert judgment; proper and improper linear models; evidence-based practice; coach-led analytics.

Contact Address

Leeds University Business School
University of Leeds
Leeds LS2 9JT, UK
Email: wjg@lubs.leeds.ac.uk

The Role of Analytics in Assessing Playing Talent

1. The Nature of Analytics

Analytics is one of the current buzz words that crops up in a wide range of contexts – business analytics, retail analytics, supply chain analytics, human resource analytics, and political analytics, to name but a few of the more frequent ones, and, of course, sports analytics. Analytics is data analysis to support decision making. It is analysis with purpose, motivated not by interesting questions but by practical questions, by questions asked by those in positions of responsibility within organisations who have to make decisions that will affect future performance. It is actionable insight, analysis that aims to make a difference, combining technical rigour with practical relevance.

Analytics (or data science) encompasses a wide range of analytical methods. Statistical analysis is at the core of analytics but other non-statistical techniques such as linear programming, cluster analysis and network analysis are all used to support decision making and so should properly be included in analytics. Indeed many would argue that analytics is just a new label for what we previously called operations research and management science. There is some substance to this argument. Ultimately what label we use is unimportant. The crucial point is that analytics (or data science or operations research or management science) is all about harnessing the power of data analysis to improve the effectiveness of decision-making processes. As will be argued in this chapter, analytics represents an evidence-based approach founded on the premise that decisions on the best course of action are more likely to be successful in terms of improved performance when all relevant available information is considered in a systematic manner rather than relying solely on intuitive judgment.

Analytics consists of the three D's – data, domain and decisions. Effective analysts need not only analytical skills but must also understand the objectives of the decision makers and the context within which they are operating. Analytics is not just about applying analytical techniques to a data set. When new problems emerge, they are often ill-understood initially and need to be structured more formally by the analyst to determine what relevant analysis is possible, what data is required, and which analytical techniques are appropriate. These analytical decisions require that the analyst and the decision maker work together. The decision maker will usually have much more knowledge and experience of the specific context and the analyst needs to utilise this expertise. So analytics is an art and a science with the effective analyst combining both technical skills and interpersonal skills.

Organisations, even those in the same sector, vary hugely in the extent to which they employ analytics. Davenport and Harris (2007) propose a five-stage characterisation of the analytical capabilities of organisations. Stage 1 organisations are the analytically impaired organisations with negligible analytical capabilities. Stage 2 organisations have localised analytics with analytics used within a small number of departments to improve one or more functional activities. Stage 3 organisations have analytical aspirations in the sense of a strategic commitment to developing a distinctive analytical capability that will act as a source of competitive advantage but are only starting the process of developing the use of analytics across the organisation supported by an integrated database. Stage 4 organisations have built an organisation-wide analytical capability with analytics viewed as an important contributor to organisational success. Stage 4 organisations are differentiated from other organisations operating in the same sector by their extensive use of analytics but analytics is not yet the

primary source of competitive advantage. Davenport and Harris reserve the accolade of “analytical competitors” to Stage 5 organisations for which analytics has become the primary driver of organisational performance with an organisation-wide imperative to continually innovate analytically in order to stay ahead of competitors.

2. Re-interpreting the *Moneyball* Story

Applying the Davenport and Harris analytical stages model to elite sports teams, it would be relatively uncontentious to claim that most teams at the start of the 21st Century were Stage 1 or Stage 2 organisations, making little use of data analysis in any part of their organisation. If sports teams were doing any data analysis, it was likely to be in the business aspects of their operations. Analysis in the sporting operation was principally video analysis. There was little if any general awareness of the possibilities for sports analytics as a source of competitive advantage. All of that changed with the publication of *Moneyball: The Art of Winning an Unfair Game* by Michael Lewis (2003) and then its release as a Hollywood movie in 2011 with Brad Pitt in the starring role.

Moneyball is the story of the Oakland Athletics in Major League Baseball (MLB) and how, under the leadership of Billy Beane, their General Manager (who was promoted in October 2015 to Executive Vice President – Baseball Operations), they utilised insights from sabermetrics (i.e. the statistical analysis of baseball) to identify undervalued players. Oakland are a small-market team with a restricted budget who view analytics as a type of “David” strategy by which resource-constrained organisations can compete effectively with resource-rich rivals. *Moneyball* focuses principally on the 2001 and 2002 seasons when the Oakland A’s had one of the lowest player wage budgets in the MLB and only around a third of that of the New York Yankees yet in both seasons qualified for the post-season play-offs. Indeed under Beane the Oakland A’s managed an incredible sequence of 16 winning seasons from 1999 to 2014 despite their small budget and regularly having to trade their best players.

So how did the Oakland A's create a sustainable competitive advantage using statistical analysis? The answer is that they took advantage of what economists call "informational inefficiencies" in the MLB players' labour market (Hakes and Sauer, 2006). Informational efficiencies occur when market traders do not use the available information as effectively as they could to determine their valuations of whatever is being traded. There are numerous reasons why traders might be inefficient in their use of information. They may be using outdated information and failing to give enough weight to new information. They may have strong preconceptions about what drives value and may ignore any contrary information. Or it may be that traders are following conventional wisdom, a sort of "pack mentality", basing their own valuations on what others consider to be the correct valuation. Whatever the causes of the informational inefficiencies, economists argue that the market process will lead these inefficiencies to be corrected over time. All it takes is one trader to realise that the available information could be used better and to make a profit from doing so. Other traders will observe that someone is gaining an advantage and try to imitate their success. Eventually the market as a whole will adopt this new more profitable approach to using the available information and the competitive advantage of the original innovator will be eliminated. At the point the market is said to be "information-efficient" until of course a trader discovers a new way to do even better in the market, initiating the process of learning and market correction again. The phenomenon on informational inefficiencies occurs in all walks of life. Indeed economists would interpret the relative age effect in talent ID resulting in a the over-representation in elite youth development programmes of those born early in the school year as a classic case of informational efficiency with insufficient weight being given to relative age within a cohort (see Wattie, Schorer & Baker, 2015).

In professional team sports, the ultimate transformation process is to convert a financial budget into sporting performance, wages into wins. Teams with a restricted wage budget can only remain competitive with resource-richer rivals by being more efficient in how they spend their budget. They need to identify value-for-money players, that is, players who will contribute more to winning per dollar of wage spend. The Oakland A's were highly efficient in using the available information to identify value-for-money players. As *Moneyball* highlights, the Oakland A's differed from other teams in two main respects. First, they relied much less on the intuitive expert judgments of scouts as to who were the best prospects and put much more weight on the performance statistics of players. Second, the Oakland A's did not rely on the traditional performance statistics that other teams looked at but instead, based on the analysis of Bill James and other sabermetricians, they used different metrics that statistical analysis showed to be better predictors of winning percentages. In particular, in the case of hitters, the Oakland A's did not focus on batting and slugging averages that measured getting to base only by hitting. The Oakland A's used on-base percentage which included not only hits but also walks. Essentially conventional wisdom had been that walks resulted from pitcher error and hence no market value was attached to the batter's ability to judge which pitches to hit and which to leave. As a result, in the MLB players' labour market, an above-average propensity to be walked to base constituted the proverbial "free lunch" since it was not factored into the market valuations of players. The Oakland A's took full advantage of this market inefficiency as the two sports economists, Hakes and Sauer, show in their 2006 study. Interestingly they also show that this particular source of competitive advantage more or less disappeared in 2004 after the publication of *Moneyball* and other teams became more aware of the market value inherent in batters with high on-base percentage, just as the market efficiency hypothesis in economics would predict. The Oakland A's had to look elsewhere for hidden value in the market.

The potential competitive gains from analytics is the key message that the world of elite sport has taken from *Moneyball* although many in the sports world remain unconvinced. However there has been much misinterpretation and misunderstanding of *Moneyball* particularly the implications for traditional scouting. People tend to forget that although *Moneyball* is based on a true story, both the book and especially the movie, represent a popularised, dramatically-heightened account of the Oakland story. There are important differences between how the Hollywood A's managed by Brad Pitt operate and how the Oakland A's managed by Billy Beane operate. Crucially the Hollywood A's are portrayed internally as a highly dysfunctional organisation with Brad Pitt and his fictional analyst in continuous conflict with the scouts and the field manager. The message of the film is that data scientists can replace scouts with recruitment decisions based on algorithms rather than intuition and experience.

The either-or, art-versus-science storyline works as a dramatic device but it does not represent the reality of the Oakland A's who retain their scouting network which is as extensive as any other MLB team. The difference with the Oakland A's is that they combine the evidence provided by the scouts with the evidence provided by the data scientists. The reality of the Oakland A's is much less dramatic than the Hollywood A's with scouts and data scientists working in tandem to provide a much more holistic input into the decision-making process. Billy Beane watches videos and goes to games to watch specific players, and combines his own subjective evaluations with those of his scouts and the metrics provided by his analysts. The message is not "don't rely on your eyes" but rather "don't rely *only* on your eyes", a subtle but crucial difference and one that is often misunderstood by proponents and critics alike.

The other misunderstanding of *Moneyball* is to see it as “one-size-fits-all” solution to resource constraints in any professional team sport. At times the proponents of sports analytics give insufficient weight to the specific baseball context of *Moneyball* and hence under-estimate the difficulties involved in transferring the insights into other sporting contexts, particularly the invasion (or territorial) sports such as the various codes of football, hockey, rugby and basketball. In the crudest form, the “one-size-fits-all” approach leads to a time-wasting search for the Holy Grail of a performance metric in a specific sport that will be akin to on-base percentage in baseball and provide the key to discover hidden value in the sport’s players’ labour market. Two important features of the baseball context need to be appreciated. First, baseball as a striking-and-fielding game is relatively atomistic in the sense that at its core is the individualistic contest between the pitcher and the batter. There is relatively little tactical co-ordination required between players. This has the important consequence that the contributions towards game outcomes of individual players are highly separable and largely independent of each other. Second, baseball involves a very high degree of skill specialisation – pitchers pitch and batters bat – so that potentially the contribution of any individual player can be reduced to a single metric. Essentially the *Moneyball* story is about getting an advantage from not only using metrics, but from using better metrics. Specifically on-base percentage is a better metric for measuring the win contribution of batters than batting and slugging averages.

Moving into the invasion-territorial team sports involves a very different context. These sports seek to emulate the battlefield with an object (i.e. a ball or puck) having to be moved into enemy-defended territory. These games have a more complex structure with players in a team having to work together either in possession to gain territory to create and convert scoring opportunities (i.e. offense) or out of possession to protect their territory and prevent

their opponents from scoring (i.e. defence). It follows that tactical co-ordination is fundamental to these types of team sports with players requiring to co-ordinate their individual actions and having to continually make spatial decisions in and out of possession as to where to position themselves with these decisions crucially dependent on the positioning decisions of their team mates and their opponents. The importance of tactical co-ordination means that individual player contributions are much more interdependent and so the win contributions of individual players are much less separable.

The other important contextual difference is that in many invasion-territorial sports, player performance is multi-dimensional with individual players required to undertake a variety of different actions in offense and defence. The degree of specialisation by individual players varies across sports with association football (i.e. soccer) towards the “generalist” end of the spectrum while American (gridiron) football is more towards the “specialist” end of the spectrum. But, irrespective of the degree of individual specialisation, it follows that the invasion-territorial sports require an array of performance metrics to capture the multi-dimensional skill sets that individual players and teams require. Any summary player performance metric must be of necessity a composite player rating that is based on combining a set of skill-specific performance metrics. Unlike baseball there is no single skill-specific performance metric that can effectively capture an individual player’s contribution to team performance and game outcome. So player rating systems in the invasion-territorial sports necessarily comprise two distinct problems, an identification problem of determining the most appropriate set of skill-specific performance metrics, and a composition (or weighting) problem of how to best combine the set of skill-specific performance metrics to construct a summary player performance rating. This goes way beyond *Moneyball* which focuses mainly on the identification problem in the context of finding the single best metrics for the two core

skills in baseball, pitching and batting. (Statistically, fielding is of minor importance as a systematic determinant of game outcomes.)

3. Expert Judgment versus Statistical Analysis

The issues facing the development of a more analytical approach to talent ID and player recruitment decisions in the invasion-territorial team sports are not unique. Indeed there is a large body of decision research on the relative merits of expert judgment and statistical analysis as the basis for decisions on the best course of action in multivariate contexts. Dawes (1988) actually tracks the antecedents of this research right back to Benjamin Franklin in the 18th Century and Franklin's proposal of the method of "prudential algebra" in which the reasons for and against each alternative course of action are identified and assigned a score of +1 or -1, respectively, with the recommended course of action having the highest net score. The findings of this research particularly over the last 60 years are remarkably consistent and very instructive for the specifics of how to most effectively utilise the contributions of coaches, scouts and data analysts.

The starting point for the modern research on expert judgment and statistical analysis as the basis for decision making is Paul Meehl's book, *Clinical versus Statistical Predictions: A Theoretical Analysis and Revision of the Literature* published in 1954. Meehl compared the findings of 20 different studies in a wide range of areas and discovered that statistical analysis always provided at least as good predictions of future outcomes, and in most cases significantly more accurate predictions, than the predictions of experts using their intuition and experience. Meehl's book, which he himself described as "my disturbing little book", provoked considerable controversy at the time and led to further studies comparing the effectiveness of experts and algorithms. This research continues. But the overwhelming body of evidence points in one direction, namely, the superiority of algorithms over experts. When it comes to man versus machines in predicting the outcomes of different courses of action, it

is as close to a unanimous verdict as could be expected in the real world. For example, Daniel Kahneman, a Nobel Prize winner and author of *Thinking, Fast and Slow* (2012) in which he surveys around 200 studies across a wide range of contexts, concludes that 60 per cent of these studies show that statistically-based algorithms produce more accurate predictions with the rest of the studies showing that algorithms are as good as the experts in the area. Dawes (1988) in his earlier review reached the same conclusion, stating that ‘the finding that linear combination is superior to global judgment is strong; it has been replicated in diverse contexts, and no exception has been discovered’. (p. 207). Yet despite this remarkable consistency in the conclusions, unparalleled in the social sciences where the multiple possible interpretations of behaviour usually means that alternative contending hypotheses continue to co-exist, Dawes laments that this research has had virtually no impact on practice with confidence in the superiority of expert judgment remaining unassailed.

The range of contexts covered by this research includes college admissions tutors predicting student performance, loan officers evaluating the likelihood of bankruptcy amongst firms applying for bank loans, clinical practitioners predicting survival rates of patients, marriage counsellors predicting marital stability, and parole officers predicting recidivism. A common finding in many of the studies is that unstructured interviews tend to lead to poorer decisions as information provided by metrics of past performance gets marginalised by interviewers who focus on the specific information that became a focal point in the interview but has limited predictive content relative to the whole body of data available prior to the interview.

It would be easy to conclude that the body of research supports Brad Pitt’s approach of looking only at the data and ignoring the scouts. But this would be to ignore the intricacies of

the decision-making process in multivariate contexts. In particular, Dawes himself, as well as comparing the relative effectiveness of expert judgment and statistical analysis, has also investigated what it is about statistical analysis that leads to more accurate predictions and better decisions. His paper on the subject (Dawes, 1979) has been described by Kahneman (2012) as ‘the most important development in the field since Meehl’s original work’ (p. 226) and, paradoxically, shows the importance of the expert in effective decision making.

Dawes (1979) investigated what we have designated above as the composition (or weighting) problem. Given an identified set of predictors, Dawes first considered the predictive accuracy of models that use a statistically-derived set of weightings to combine the individual predictors and then compared these with models that use non-statistically-derived weightings. The statistical models are called “proper linear models” and use multiple regression analysis to derive the optimal weights. Dawes compared the predictive accuracy of these statistical models with what he called “improper linear models” in which the weightings are either randomly selected from normal or rectangular distributions, or set to be equal (as in Franklin’s prudential algebra method). Dawes undertook 20,000 simulations and found that randomly-selected weightings worked almost as well as the optimal weightings produced by multiple regression analysis, and equal weightings worked even better.

The remarkable effectiveness of improper linear models particularly the use of equal weights recasts the algorithms-versus-experts debate in two ways. First, it emphasises the importance of the identification problem and being able to comprehensively identify all of the factors influencing the behaviour patterns and future outcomes with which the decision maker in a specific context is concerned. And this reasserts the importance of the expert in using their

knowledge and experience of the specific context to identify the factors to be included in the algorithm. Second, when it comes to the role of statistical analysis, it shows that the most important contribution is the consistency with which information is combined across all the alternatives. The use of optimal weightings derived statistically, equal weights or some other weighting system is of secondary importance. Critically experts should not over-ride algorithms with a special-case argument to impose different sets of weights in evaluating alternative options. It is the consistency of linear models both proper and improper models that Dawes has shown to be critical to effective decision making.

‘What can be concluded is that the procedure of looking first within each variable and then comparing across by some weighting system is superior to that of making global intuitive judgments across variables regarding each choice in isolation.’ (Dawes, 1988, p. 222)

4. Player Rating Systems with Multiple Performance Metrics

As previously discussed, as soon as we move into the invasion-territorial team sports, there is a need to develop player rating systems that combine multiple performance metrics. Applying the findings from decision research, most prominently Meehl, Dawes and Kahneman, the key argument for using player rating systems is that they ensure consistency in the comparison of all players. The actual weightings used to combine the multiple performance metrics into an overall player rating is a secondary concern.

However, before downgrading the role of multiple regression analysis in constructing player rating systems, it is important to recognise the dual roles played by the estimated regression coefficients. So far, the discussion has focused on the role of the estimated regression coefficients in optimising the relative importance of the individual predictors of future performance. In this context formally optimising implies choosing estimated coefficients to create the line of best fit that minimises the sum of the squared deviations between the predicted and observed performance levels. The line of best fit optimises predictive accuracy relative to the sample data used to estimate the regression. Provided that the sample is representative, the estimated regression is applicable to the population as a whole. However, there is always the constant danger of data mining and overfitting where models of ever increasing complexity with more and more predictors are developed to increase the goodness of fit for the sample data but these models can become sample-specific and eventually begin to lose general applicability. This is one reason why improper linear models especially equal-weights models are often as accurate in their predictions as proper linear (i.e. regression) models. Using equal weights ensures consistency but avoids using weights that have been derived from one specific sample.

But regression coefficients play another role apart from optimising the relative importance of individual predictors. Regression coefficients also control for differences in the units of measurement across the predictors. This is an important consideration in player rating systems particularly when often the individual performance metrics are of two broad types with very different units of measurement. Performance metrics can often be categorised as either activity levels or success ratios. Activity levels are tally counts of the frequency with which a player has performed a specific action such as the number of attempted passes, the number of attempted tackles and the number of shots at goal. By contrast, success rates show the proportion of successful outcomes relative to the total number of attempts and are often reported as percentages. Pass completion, tackle success and shot accuracy are all examples of success ratios. Given the very different units of measurement involved in activity levels and success ratios, it follows that any useful player rating system must allow for these measurement differences as well as taking account of relative importance considerations.

So, even if the equal-weights approach is adopted to develop a player ratings system that combines a number of skill-specific performance metrics, this is insufficient on its own. The skill-specific performance metrics need to be standardised before being combined into a composite player rating. The most frequently used method of standardisation is Z-scores in which each performance metric is expressed as a deviation from its mean value divided by its standard deviation. An example of the use of Z-scores in sport is Severini (2015) who uses Z-scores to compare the top receiving performances in the NFL across seasons. So one way of implementing the equal-weights approach is to adopt a two-stage approach of first

standardising the individual performance metrics using Z-scores and then adding together the Z-scores for each individual player to calculate an overall player rating.

In my own work in developing player rating and valuation systems in association football, I have used both proper and improper linear models. Gerrard (2001) proposes a measure of player and team quality that utilises weights derived from a regression analysis of football transfer fees. These estimated coefficients show the relative importance of the various indicators of playing quality as reflected in transfer fees as well as controlling for the different units of measurement. The indicators of playing quality include age, career league experience, current appearance rates, career and current scoring rates, international appearances, and the size and status of the player's current team. In contrast, I have developed an improper linear variant of the football transfer fees model called the *SOCCKER TRANSFERS* player valuation system (Gerrard, 2004) in which the original regression model is consolidated into seven composite value predictors converted into a common logarithmic scale and then added together on an equal-weights basis.

The implications for talent ID and assessing the development of youth players are very clear. An effective player rating system must be comprehensive which requires that it includes metrics that capture all of the relevant factors and these metrics must be combined in a consistent manner. The expertise of coaches and scouts is the crucial starting point for determining the relevant factors that are able to identify young talented players with the highest success probabilities of a career at the elite level of their sport. In this discovery phase, the analysts play a secondary role in formulating the precise metrics to measure the relevant factors as well as validating the degree to which these metrics are predictive of

future career success. Having agreed the set of metrics to be used to identify young talent players and track their development progression, the analyst then has the task of developing a composite rating that brings together all of the metrics. The findings of decision research suggest that the rating system does not necessitate the use of sophisticated statistical multivariate techniques such as multiple regression. Simple can prove best. So long as the various metrics have been standardised to be directly comparable, simply adding them together may suffice. Standardisation could involve converting all of the metrics to the same point-scale or to Z-scores. A comprehensive player rating system constructed in this way will provide a basis for consistent comparisons between players and over time. And crucially the greater the involvement of the coaches and scouts in the initial discovery phase, the greater the likelihood of buy-in from the coaches and scouts in using the rating system to assist in their decision making. If used properly, a player rating system provides a first cut in reaching decisions about the future career potential of young players. There may be other, more intangible factors not directly included in the rating system that although difficult to measure are still important and need to be included in final decision. Crucially if such considerations are to be included they should be done so for all players in a similar fashion to maintain the consistency of the decision-making process.

5. Overcoming the Clash of Cultures in Elite Sports

Moneyball, particularly as depicted in the Hollywood movie, while highlighting the possibilities for data analytics in the player recruitment decisions in elite team sports, does so in a way that represents the data scientist as an alternative to the traditional scout. The clash of cultures, art versus science, man versus machine, creates the dramatic tension that runs throughout the movie with analytics ultimately winning the day, captured in the moment when the home run that seals the A's record-breaking 20-game winning streak is scored by a player recruited on the basis of his statistics in the face of opposition from the scouts. By reinforcing the stereotypes of the analyst who only knows the statistics taking on the scouts and coaches who know the game, *Moneyball* may have been counter-productive in persuading teams to be innovative in embracing analytics and becoming analytical competitors in the Davenport and Harris taxonomy. Indeed Hollywood followed up *Moneyball* with an anti-analytics baseball movie, *Trouble with the Curve*, starring Clint Eastwood in which traditional scouting triumphs by detecting a fundamental flaw in the batting technique of a first round draft pick with great metrics as well as discovering a great pitching prospect for whom there is no data and so would never register on the analyst's radar.

Decision research does seem on first reading to side with the analytical approach to player recruitment and talent ID but, as this chapter has argued, the work of Dawes in particular supports what I call coach-led analytics and the need for teams to adopt an evidence-based approach that combines expert judgment and statistical analysis. As Pfeffer and Sutton (2006) put it, 'evidence-based management is conducted best not by know-it-alls but by managers who profoundly appreciate how much they do not know'. (p. 72) Whether it is the coach who

knows it all or the analyst who knows it all does not matter, neither is conducive to an evidence-based approach. Coach-led analytics utilises the coach (or scout) as the expert best able to identify a comprehensive set of player characteristics that predict future performance. But what Dawes shows is that expertise in the identification problem does not translate into expertise in the composition problem. Indeed expertise in identifying performance predictors often gets in the way of applying consistency in combining these performance predictors. Coaches and scouts have a tendency towards inconsistency by rating individual players individually, giving more weight to certain predictors for some players but not all. The evidence clearly shows that this subjective and selective application of algorithms is likely to diminish rather than enhance the effectiveness of the decision-making process. Hence the key lesson from decision research that algorithms whether statistically-based or applying equal weights to standardised metrics are the best way to support decision makers. Effective decision making is an art and a science. Analytics has a key role to play in supporting coaching decisions but so too has the experience and expert judgment of the coaches and scouts. The most successful teams are likely to be those that can combine effectively both sources of input into the decision calculus.

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