TITLE:

The application of expected points in rugby union: proposal of a novel framework.

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Note: This is a pre-print file yet to be submitted for peer-review.

Please cite as; Fitzpatrick, B., Nolan, D. (2024). The application of expected points in rugby union: proposal of a novel framework. SportRχiv.

Abstract:

Expected points (xP) is a statistical measure that quantifies the likelihood of teams scoring or conceding points during competition, and has been applied in various ways across multiple sports. To date, a framework for the application of xP in rugby union has not been explored. This paper discussed the application of xP in sports performance analysis and developed a model that may be used within performance analysis in rugby union. Examples were presented to illustrate the application of the proposed novel method in aiding performance measurement and tactical decision making. This method of analysis could introduce a novel approach to performance analysis in rugby union, and provide insightful data which can aid coaches in real-time decision making during competition.

Keywords:

Expected points, rugby union, performance measurement, decision making

1. Introduction:

The concept of Expected Points (xP) is a statistical measure that quantifies the likelihood of teams scoring or conceding points (Rathke, 2017). Variations of this metric have been employed across different sports, each with its unique nomenclature and calculation method, which will be elaborated upon subsequently. For instance, in sports where the primary objective is to score goals, such as ice hockey or soccer, a similar statistic is referred to as Expected Goals (xG). In golf, a comparable metric is known as shots gained (SG). In American football, xP is determined by calculating the average number of points a team scores from certain possessions on the field (Romer, 2002). For instance, if a scenario of "3rd and goal" with five yards remaining occurred a thousand times and resulted in four thousand points, the expected points for that situation would be four. However, in sports where the focus is on shot taking, such as ice hockey, basketball, or soccer, the calculation of this metric differs. The value is contingent on the location from which the shots were taken. For example, in the 2021-22 NBA season, the success rate for Free Throws was 77.5%. Consequently, two free throws following a foul would have an expected value of 1.55 (0.775 + 0.775) (*Statmuse.com)*. These sports often incorporate additional factors into their calculations, such as the number of defenders in proximity to the ball or the level of pressure exerted on the shot taker.

The implementation of metrics such as xP or xG in sports has proven beneficial and serves as a reliable tool for measurement (Rathke, 2017), tactical modifications (Romer, 2002), recruitment strategies (Kharrat, McHale and Peña, 2020), and predictive analyses (Noordman, 2019) However, to the best of the authors' knowledge, there has been no attempt to adapt the xP model to the sport of rugby union. This paper aims to present a review of the use of xP in sports performance analysis and introduce an innovative application of the xP framework to rugby union, proposing a model for creating such a system substantiated by real-world examples to establish its validity.

2. Applications of xP in Sports Performance Analysis: A brief review

Baumer, Matthews, and Nguyen (Baumer, Matthews and Nguyen, 2023) identified the measurement of a game state's expected value as one of the four major ideas in Sports Analytics. The concept of xP or xG has been evolving in sports prior to 1971 (Carter and Machol, 1971), with American football and baseball in 2006, and association football and ice hockey in 2012, being early adopters within their respective sports. xP serves as a metric for scoring efficiency in sports by contrasting team-level conversion rates with the average group-level conversion rate in specific scenarios.

In sports such as American football and baseball, the number of "states" that a possession or batter can encounter is limited. For instance, in baseball, each of the three bases can be either occupied or vacant, and there are a finite number of three outs, resulting in 24 potential scenarios a batter can face. These states in baseball are often short-handed to *Out, 1st base, 2nd base, 3rd base*, so with 2 outs used and 2 baserunners on 2nd and 3rd base it would be written as "2 outs, _2b,3b". The performance evaluation of players and teams can be based on their ability to improve the state they encounter in a given situation. In baseball, the ability to compare the average runs expected from different states has led to a significant decrease in the use of sacrificial bunting in the MLB, except under specific circumstances (Chandler, 1997). In low-scoring sports such as soccer and ice hockey, teams traditionally compare their performance based on metrics such as wins versus losses and the number of goals scored. However, the issue with using goals as a measure in low-scoring sports is that they can be infrequent and inconsistent.

The rationale behind introducing xP in such sports was to establish a more consistent performance metric, as the number of shots taken in a game significantly outnumbers the goals scored or wins/losses per match. It was observed that teams that took more shots tended to win more frequently than those that did not (Jlikens, 2011). However, using metrics such as shots, shots on target, or variations such as the Fenwick Rating and Corsi Rating has its limitations. These shots could potentially be taken from long distances, making them less likely to result in scores (Macdonald, 2012). To address this, MacDonald developed an xP metric for ice hockey that demonstrated a higher correlation with predicting performance. McDonald's method had greater correlations ($R^2 = 0.69$) for goals in the 2nd half of the season vs the next highest model which was the Corsi Rating ($R^2 = 0.51$). This led to higher values being attributed to more advantageous shots that were initially determined primarily by the pitch location variable but have since advanced to include variables such as number of defenders in vicinity as well. Distance and angle were the primary variables considered in McDonald's study. Distance, in particular, was initially deemed the most important variable in shot-based sports; however, this notion has been refuted as an accurate singular indicator for an xP metric (Rathke, 2017). Angle is typically a crucial variable in shot-taking sports with a forward-facing goal, such as lacrosse (Myers *et al.*, 2021) and field hockey (Myers and Daly, 2022). Myers found in lacrosse, that for each degree in increase, that scoring chances improved by 6% and for each meter further away, the chances of scoring decreased by 5%. Similarly, in American Football, distance was found to be an indicator, but not a straightforward linear relationship (Alamar, 2010). The calculation was performed by dividing the number of goals previously scored from a shot at a particular location by the number of shots taken from that location. This calculation assigned a value to a single shot. For instance, a shot taken 5m directly in front of the goal in soccer would have a higher xG of 0.6xG, indicating a 60% chance of scoring (Schmidt, 2020), while a shot from the penalty spot would have a 0.25xG, or a 25% chance of scoring.

Numerous other variables have been considered and disregarded in different models, such as distance from the goal, the player taking the shot, whether the shot was taken with their head, weaker or stronger foot, and the number of defenders between the shot taker and goal (Rathke, 2017). Sports such as basketball and golf have also adopted similar approaches to the use of expected points models. In basketball, these models have been instrumental in assigning values to shots taken from specific areas on the court. This has led to tactical advancements, with the proportion of 3-point shots out of the total shots increasing from approximately 22% between 2008 and 2012 to 39% in 2021 ('NBA League Averages - Per Game', no date). Golf utilised the 'Shots Gained' metric to reveal a stronger correlation between world rankings and shots gained from the tee than from putting. This challenges the old adage, "drive for show, putt for dough." Influenced by this insight, professional golfers have emphasised strength training with the intention to increase their swing speed and drive the ball further (Short, 2020).

In both golf and basketball, these metrics have facilitated the analysis of individual performance in specific aspects of the game, such as 3-point shooting in basketball and driving length in golf. There has been efforts to consider expected points from an individual point of view in team sports as well although it is considered difficult to do accurately (Gerrard, 2005). Interestingly, this has not been found in association football (Tippett, 2019), where consistently creating more xG seems to have a longer-term benefit than merely outperforming one's xG.

Miller and colleagues (Miller *et al.*, 2014) introduced the concept of using xP not only to measure scoring but also to evaluate in-play decisions in basketball. xP was employed to determine the best decision for a ball handler – to shoot, pass, or drive. Passing to a player in open space with a high-value shot would yield a positive change in xP value. In this case, the use of xP allows the passer to be credited with a positive effect on the game, whereas traditional basketball stats would only credit the passer if the shot is successful. xP models also serve predictive purposes. In sports like soccer (Mead, O'Hare and McMenemy, 2023) and ice hockey (Macdonald, 2012), xG have been found to be a better predictor of future performance than actual goals scored. However, combining expected goals with actual goals scored further enhances the predictive accuracy.

In soccer, teams and players that outperform their xP (Vs xP) are unlikely to repeat this overperformance in the following season (Tippet, 2019). The contrast between 'xP' and 'Vs xP' is intriguing, and warrants further research in other sports to understand the commonalities and causes of this phenomenon. In field hockey, a study of the USA Division 1 found that xG did not add any significant predictability beyond shots per Game or Shots on Target per game. This suggests that xG might not be as useful in field hockey owing to the increased data collection and formulation required to produce an xG stat (Myer & Daly, 2022). However, it is possible that a different xG model, perhaps one with more variables as opposed to Myer's model, could yield different results.

xP models have also influenced recruitment strategies in sports, with soccer clubs like Brentford and Midtjylland acknowledging their use of xG to aid in player recruitment (Hoog, 2015). However, xP models have been criticised. Some critiques include a lack of depth in the analysis of the reliability and validity of these models (Tiippana, 2020), such as not considering enough variables (Mead, O'Hare and

McMenemy, 2023) or overstating their importance or use. Misunderstanding the purpose of a metric is another common criticism. xG is not overly accurate in predicting a single shot being a goal or the winning of a match (Eggels, Elk and Pechenizkiy, 2016), but is more accurate as a longer-term indicator (Mead, O'Hare and McMenemy, 2023). More mathematical concerns revolve around overfitting or under sampling of data, particularly in relation to rare occurrences in certain sports such as goals from specific locations.

For instance, a goal may have been scored from 53m in front of the goal but not from 51m. Modellers would need to decide whether to group areas into categorical bins, such as 5 or 10m squares, or use more precise pitch locations. This decision involves a trade-off between more precise data and the need for a larger database to achieve accuracy. One solution to increase the precision while measuring in more precise categorical bins involves the use of calibration techniques. Platt's scaling and Isotonic regression have been recommended as appropriate calibration techniques (Eggels, Elk and Pechenizkiy, 2016). It has been suggested that Platt's scaling is better for small data sets, while isotonic regression is more suitable for larger datasets of 1000 or more events (Caruana and Niculescu-Mizil, 2006).

Table 1. The application of xP in various sports.

SPORT	METRIC	METHOD OF CALCULATION
BASEBALL	Expected Run Value (ERV)	*Number of runs scored / Number of times this state occurred in MLB data*
BASKETBALL	Expected Points (xP)	*Points scored from position on court / shots taken from position on court*

AMERICAN FOOTBALL	Expected Point Value (EPV)	*Points scored from x state (yards remaining, down, yards to first) / number of occurrences of x state*
SOCCER	Expected Goals (xG)	*Goals scored from position on pitch / shots taken from position on pitch*
ICE-HOCKEY	Expected Goals (xG)	*Goals scored from position on pitch / shots taken from position on pitch*
GOLF	Shots Gained (SG)	*Number of shots taken from x yards from pin / number of occurrences of shots being x yards from pin*

3. Application of a novel xP framework in Rugby Union Performance Analysis

In sports such as ice hockey, soccer, and basketball, the xP models primarily focus on shots. However, rugby's primary method of scoring is through tries, with additional points coming from kicks at goal during dead ball situations (penalties and conversions) or in-play through a drop goal.

Traditionally, goal-kickers in rugby have been evaluated on the basis of their success percentage. This is evident on the United Rugby Championship website, where the first statistic shown for goal-kickers is their goal-kicking success % (*Players Statistics - United Rugby Championship*, no date). However, this measurement method has several drawbacks. For instance, when comparing equally skilled goal kickers, some may have had more kicks from difficult positions than others who may have had a majority of relatively easy kicks. -xP for kicks at goal in rugby could be calculated using similar methods as those used in ice hockey, football, and basketball. Quarrie & Hopkins (Quarrie and Hopkins, 2015) conducted research on the impact of kick difficulty in evaluating a goal kicker in rugby, as well as the influence of the score and time remaining on the clock. However, their study did not explicitly mention the term 'expected points'. Quarrie & Hopkins investigated further variables such as venue and importance of the kick based on the scoreline. They found that venues such as Loftus Versfeld at high altitude in Pretoria, South Africa had a 4% higher success rate than average, attributed to the thinner air the ball travels through meaning kickers can kick further. That matches up with their findings that for rugby goal kicking, distance was a more impactful variable than angle. Their kick importance model where they multiplied the kick difficulty based on the scoreline with kicks in tight games being considered more important than kicks where a team is well ahead. This is a thought leaning towards win probability models we see in Romer (2002). This is in contrast to the Markov models seen in Goldner (2012). Markov models assume the previous actions have no impact on the proceeding action which is easier to measure and therefore more scalable and applicable in practical situations comparably introducing more variables which would be considered more valid.

3.1 Scoring and Performance Measurement

3.1.1. Goal Kicking

Goal kicking opportunities in rugby include conversion attempts and penalty kicks, which occur after a try has been scored or a penalty awarded. With the application of xP, a value can be assigned to the kicks from specific locations on the pitch. This can be calculated using a historical database or linear regression to predict the likelihood of an average kicker successfully making a kick from a specified location.

For instance, a conversion kick worth two points taken 5m from the left touchline might have a predicted success rate of 50%. This would give the kick attempt an xP of one point (2 points × 50%). With this information, we can evaluate the kicker's performance against the xP of the kick;

Value – Expected Value

Successful Kick: 2 points – (2 points x 50%) = 2 points – 1 point = 1 point Vs xP

Unsuccessful Kick: 0 points – (2 points x 50%) = 0 points – 1 point = -1 point Vs xP

If this hypothetical kicker successfully made six out of ten kicks from this position, they would have a positive "Vs xP" of one point. A positive "Vs xP" for two points suggests that this is a proficient goal kicker. However, a 60% success rate would be considered subpar for a kicker at the international level given that the average success rate during the 2022 Six Nations was 75.4% (104 successful kicks out of 138 attempts).

For instance, in the case of Italy during the 2022 Six Nations, the authors computed a success rate of 72.2% (13 successful kicks out of 18 attempts) from the tee, but their kicks at the goal had an average distance of 38.8m. In contrast, Wales had a higher success rate of 81.3% (13 successful kicks out of 16 attempts), but their kicks at goal had a shorter average distance of 24.9m. Enhanced measurement of goal kickers may allow coaches to make more informed selection and teams to make better recruitment decisions.

3.1.2. In Play

Rugby teams can utilise xP as a performance measurement tool, comparing their efficiency in converting possessions into points against an average team in an expected point database. Similar to the states used in Baseball and NFL, each possession in rugby could be assigned a value based on the points scored from that possession in a historical database. For instance, considering lineout attacks, by summing the values from each lineout possession a team had, one could estimate the number of points they should have scored. This approach would provide a more nuanced understanding of a team's performance, considering the quality of their opportunities, not just the quantity;

Value – Expected Value

Try with conversion: 7 - xP

Try without conversion: 5 - xP

Drop Goal: 3 - xP

Penalty that leads to a Successful Kick at goal: 3 – xP

Other outcome: 0 – xP

Indeed, if a team's expected points across their 60 lineouts over five games were 30 points, and they actually scored 45 points, you could interpret this as a team having a strong lineout attack. They scored 15 points more than the average team that would have scored from the same opportunities.

Conversely, another team with the same number of lineouts may have scored only 15 points, which was 15 points less than the average. This suggests that their lineout attacks were less effective. The use of expected points in this way provides a more nuanced understanding of a team's performance, considering the quality of their opportunities, not just the quantity;

Team Scores 45 points vs xP of 30

Value – Expected Value

+15 Vs xP

Team Scores 45 points vs xP of 30

Value – Expected Value

+15 Vs xP

Teams with stronger scoring performance from lineouts might choose to maintain their current tactics in this area and focus on improving other aspects of their game. On the other hand, a team with weaker lineout performance could use this information to make various adjustments, such as changing tactics, altering player selection, recruiting new players or coaches, or redesigning their training regimens. Tactically, a team could modify their strategies to try to score more often in this scenario, or they could devise a strategy to avoid this situation. For instance, a team scoring poorly on lineouts might opt for different penalty options. They could utilise the tap penalty or scrum options more frequently or attempt a penalty kick at the goal rather than kicking the ball to touch as often. These adjustments can potentially enhance their overall performance by optimising their strategies based on their strengths and weaknesses.

3.2 Tactical Decision Making

As previously discussed, the use of xP metrics has led to significant tactical adjustments in various sports, such as a decrease in mid-range shooting in basketball, reduced sacrificial bunting in baseball, and increased 4th down attempts in the NFL. We now explore how this logic can be applied to rugby.

In rugby, when a team is awarded a penalty, it has several options: it can attempt a 3-point penalty goal kick, punt down the touchline to set up an attacking lineout, opt for a scrum on the spot, or take a tap penalty on the spot where the penalty was awarded. For instance, if a team is awarded a penalty in front of the posts about 18m away, and we estimated a 95% chance of scoring when taking the 3-point penalty goal kick, the expected value of this decision would be 2.85 points (3 points × 95%). For comparison, if we estimate a 25% chance of scoring 7 points from a lineout 5m out (should the team kick to touch), this would yield an expected value of 1.75 points (7 points x 25%). In this scenario, the calculation suggests that the team would be better off attempting a penalty goal kick. However, if the penalty goal kick was more difficult, say with a 50% chance of success, the expected value of kicking at goal would be 1.5 points (3 points x 50%). In this hypothetical situation, it would be more advantageous to opt for a lineout. This demonstrates how xP can guide tactical decisions in rugby, similar to its impact on other sports.

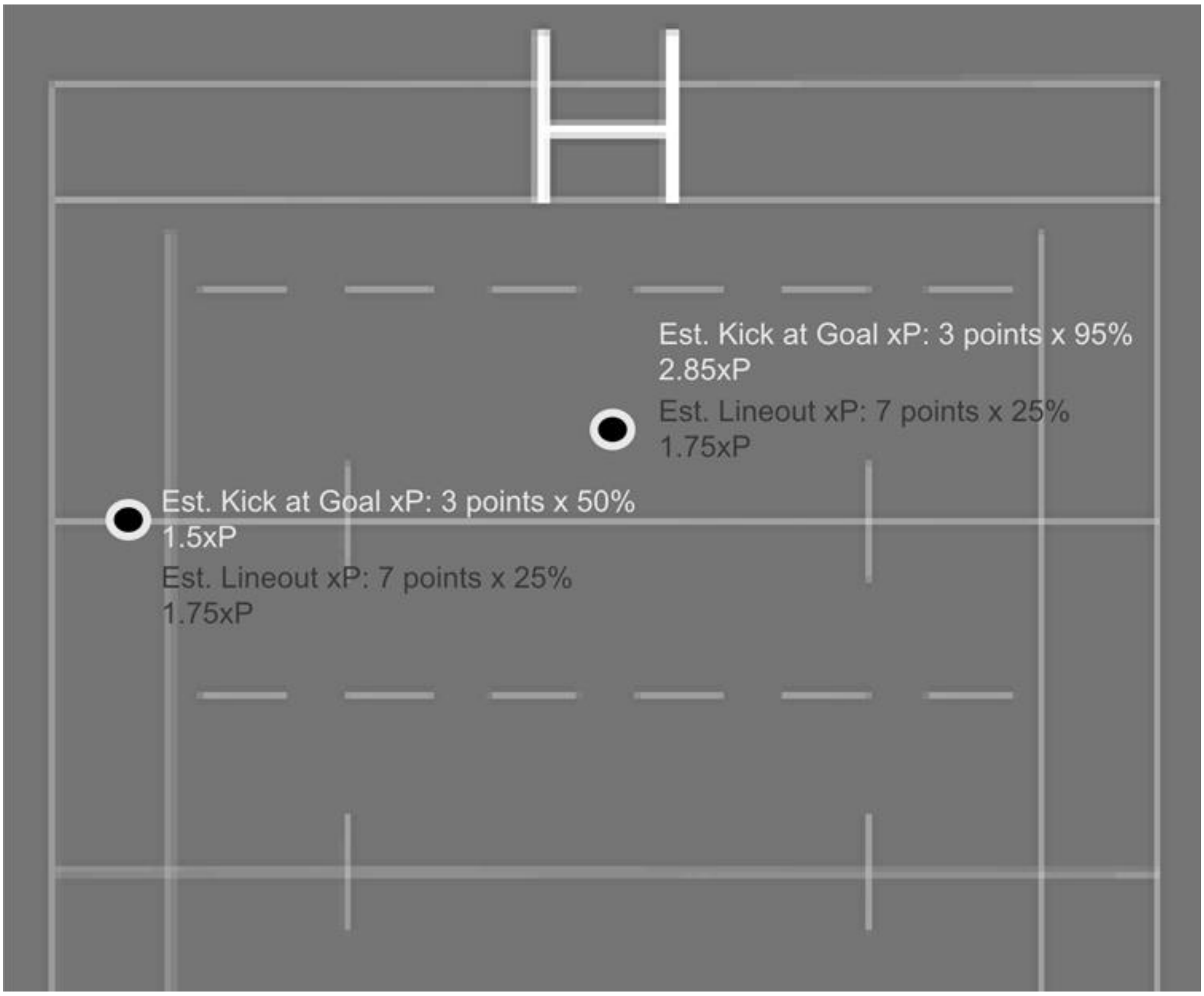

Figure 1. Illustrative example of application of xP in rugby union

While xP provides a valuable framework for decision making, it is important to remember that there are other factors to consider. These include the potential loss in field position, the current score and time remaining in the half or match, the strengths and weaknesses of the team, and possible secondary outcomes.

One unique aspect of rugby is that there are instances where teams deliberately give up possession of the ball by kicking it forward with the aim of gaining territory. In these situations, teams must decide whether to kick the ball at all or run, and if they choose to kick, what type of kick should be made. Thus, xP research can influence these decisions. For instance, a team might have to decide whether to kick the ball in a straight line up the pitch or to make an angled kick to touch, thereby creating a lineout – a contestable possession. The choice between these options can be informed by an xP analysis that considers the potential point outcomes of each decision. Individual and collective skill of teams would also have an impact on this decision.

xP can help identify the inflection point at which one strategy becomes more advantageous than the other. This decision-making process is illustrated using the hypothetical xP data below. By comparing the expected points for each strategy under different conditions, teams can make informed decisions that maximise their potential scoring opportunities. This approach could be particularly useful in close games where every decision can have a significant impact on the final outcome.

Table 2. Illustrative example of the application of xP in tactical decision-making.

Starting position from try line (m) for a receiving team	xP of lineout from position	xP of Kick Return from position
75-80	1.00	2.00
70-75	0.95	1.70
65-70	0.90	1.40
60-65	0.85	1.10
55-60	0.80	0.80
50-55	0.75	0.70
45-50	0.70	0.60
40-45	0.65	0.50
35-40	0.60	0.40
30-45	0.55	0.30

In this hypothetical scenario, we consider two kickers, A and B, both kicking from their 10m line, 15m from touch. Kicker A can kick the ball 30m, and Kicker B can kick the ball 60m.

For Kicker A, they have the option of kicking the ball straight up the pitch to reach the 60-65m zone. This would result in an expected point value of 1.10 for the opposition. Alternatively, they could kick the ball to touch, achieving a vertical distance of 22m if they landed it 5m into touch. This would place the ball in the 65-70m zone, resulting in an expected point value of 0.90 for the opposition. Based on these data, it would make more sense for Kicker A to kick to touch, as it results in a lower expected point value for the opposition.

For Kicker B, they have the option of kicking the ball straight up the pitch to reach the 30-35m zone. This would result in an expected point value of 0.30 for the opposition. Alternatively, they could kick the ball to touch, achieving a vertical distance of 57m if they landed it 5m into touch. This would also place the ball in the 30-35m zone, resulting in an expected point value of 0.55 for the opposition. Based on these data, it would make more sense for Kicker B to kick long and straight, as it results in a lower expected point value for the opposition. This example illustrates how expected point values can inform tactical decisions in rugby, helping teams maximise their scoring opportunities and minimise those of the opposition.

4. Conclusion

Decision-making is a critical and highly valued aspect of rugby, but as of now, there is no specific metric for measuring decisions, even in static events such as penalty decision-making, where there are opportunities for optimisation. Given the high variety of states that can occur in rugby, overfitting the data is a significant consideration when creating xP values. This ensures that the model is not too complex and does not fit too closely to the specific dataset used for training, which could limit its predictive accuracy for new data.

The potential of xP in rugby as a performance-measurement tool is considerable. It allows teams to focus on specific parts of their attack or defence as areas for improvement and dedicate further training time to these areas. This could also be useful for recruitment, with teams targeting recruits from other teams demonstrating high success in areas where they are weak. Beyond its basic use, there is ample scope for further development of the concept of xP. This could involve extending it to phase play, adjusting xP values based on weather conditions, and even considering the strength of the opposition and individual players. Such advancements could provide even more nuanced and valuable insights for teams seeking to optimise their performance.

There are limitations to potentially using xP in rugby. The biggest obstacle to using expected points in rugby is the access to the data which may be provided by some businesses but will be very difficult for individuals to replicate. Providing data is beyond the scope of this "_<adjective – "exploratory?">___" article. The accuracy of said data would also be a limitation for a creating accurate models. There are practical limitations too in that professional rugby staff may initially not understand the concept, this could conceivably lead to coaches over or under interpreting data.

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