Team performance indicators that predict match outcome and points difference in professional rugby league

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Performance indicators allow for the objective quantification of performance (Vogelbein, Nopp & Hokelmann, 2014), however, limited PI research for professional rugby league exists (Cupples & O'Connor, 2011). Therefore, this paper assessed twenty-four relative variables (home value minus away) from all 27 rounds of the 2012, 2013 and 2014 European Super League seasons, collected by Opta, amounting to 567 matches. Backwards logistic (match outcome) and linear (points difference) regression models were used alongside exhaustive Chi-Square Automatic Interaction Detection (CHAID) decision trees to identify performance indicators (PIs) and key performance indicators (KPIs). Teams had a higher chance of winning and would gain more points when they scored first (OR=1.6, β=2.4) and increased completed sets (OR=1.2, β=1.2) by one unit. Conversely, teams had a lower chance of winning when they increased scoots (OR=0.9. β= -0.2). However, some variables which were thought to be important (as identified by previous literature) were removed from the analysis thus calling into question the appropriateness of stepwise methods. Future research may consider utilising dimension reduction techniques when analysing large datasets that encompass multiple variables.

Keywords: performance indicators, rugby league, regression, decision trees.

Introduction

Gabbett (2005) recommended performance analysis as a technique for understanding rugby league (RL) although there is little research evidence to support this conjecture. Most research in RL has focused on anthropometric and physiological qualities of players (Morgan & Callister, 2011), physical collisions and injury rates (Gabbett, Jenkins & Abernethy, 2011) and time-motion analysis (Twist, Highton, Waldron, Edwards, Austin & Gabbett, 2014). Kempton, Kennedy and Coutts (2016) used PA to show that possessions which began closer to the opponent's try line, gained more points compared to regaining the ball in other areas (see also Reep & Benjamin, 1968).

Cupples and O'Connor (2011) qualitatively determined position specific PIs in Australian elite youth rugby league using the Delphi method to categorise coaches' answers to questionnaires.

Hughes and Bartlett (2002, p.739) defined a performance indicator as "…a selection, or combination, of action variables that aims to define some or all aspects of a performance". PIs are thought to facilitate the objective quantification of performance (Vogelbein, Nopp & Hokelmann, 2014) where analysts and coaching staff can use them either comparatively i.e. with opponents or past performances, or in isolation (Hughes and Bartlett, 2002). By reporting or analysing data without context the results and interpretation of data is limited and can sometimes be misleading (Hughes and Bartlett, 2002). Similarly, converting absolute data to relative can provide a better understanding of the difference between two team's performances, known as "descriptive conversion" (Ofoghi, Zeleznikow, MacMahon and Raab, 2013). Robertson, Back and Bartlett (2016) advocated this method for preparing for matches by including the opposition in the analysis; although it is more common for research papers to use absolute values (e.g. Higham, Hopkins, Pyne & Anson, 2014a; Lago-Penas, Lago-Ballesteros & Rey, 2011; Villarejo, Palao, Ortega, Gomez-Ruano & Kraak, 2015).

Whilst Hughes and Bartlett's (2002) paper has been widely viewed (18,050 views on Journal of Sports Sciences website, 21/10/2017) and cited (258 citations, Web of Science, 21/10/2017) it appears that their suggestion of providing context to an action variable to enable it to be a performance indicator have been interpreted differently. Action variables have been described as PIs when they had not been contextualised (Kajmovic, Kapur, Radjo, & Mekic, 2014; Scholes & Shafizadeh, 2014; Villarejo, Palao, Ortega, Gomez-Ruano & Kraak, 2015), context provided for some not all (Campos, Stanganelli, Campos, Pasquarelli & Gomez, 2014; Carroll 2013; Castellano &

Casamichana, 2015; Castellano, Casamichana & Lago 2012; Graham & Mayberry, 2014; Higham, Hopkins, Pyne & Anson, 2014a; Higham, Hopkins, Anson & Pyne, 2014b; Lago-Penas, Lago-Ballesteros & Rey, 2011; Meletakos, Vagenas & Bavios, 2011; Najdan, Robins & Glazier, 2014; Vahed, Kraak & Venter, 2014) or correctly labelled (Robertson, Back & Bartlett, 2016; Robertson, Gupta & McIntosh, 2016). O'Donoghue (2008) suggested key performance indicators had higher correlations with principal components; Bremner, Robinson & Williams (2013) suggested they were more significantly related to success and Shafizadeh, Taylor & Penas (2013) provided no definition or evidence. This paper will consistently define performance variables as either 1) an action variable that has not been contextualised; 2) a PI, a variable that has been contextualised and can therefore be informative of performance; 3) a key PI, a variable that is associated with successful or unsuccessful performances (e.g. correlation coefficient between >0.3, effect size >0.5, or $p<0.05$).

Sports performance has consistently been shown to be affected by contextual variables. For example, Harrop and Nevill (2014) found that League One soccer teams were 80% less likely to win playing away than playing at home. Similarly, team and opposition quality have been found to have an important influence on performance (Castellano & Casamichana, 2015; Jones, James & Mellalieu, 2004; Lago, 2009; Lago-Penas & Dellal, 2010; Lago-Penas, Lago-Ballesteros & Rey, 2011; Taylor, Mellalieu, James & Shearer, 2008; Vogelbein, Nopp & Hokelmann, 2014). Team quality has often been categorised using the previous season's final league position with teams then categorised as strong, weak, top 3, bottom 3 etc. and has been shown to influence match difficulty in rugby union (Robertson & Joyce, 2015). However, Carling, Wright, Nelson and Bradley (2014) suggested that this method could be considered arbitrary or unfair as teams could, for example, miss being classified as a strong team by just a few points, despite having been in the top three for the majority of the season. They suggested using league ranking (ordinal measure), at the time a match was played, as a more indicative measure of a team's current performance.

Logistic regression has been used to determine PIs in Australian rules football (Robertson, Back & Bartlett, 2016), match difficulty in rugby union (Robertson & Joyce, 2015) and PIs in soccer (Harrop & Nevill, 2014). The odds ratio provides a measure of how performance on each variable effects the chances of winning when the variable increases by one unit. The disadvantage of this approach is that the dependent variable, match outcome, is dichotomous (win or loss) and does not distinguish between small and large wins, potentially very different matches in terms of performances. Alternatively, the final points difference has been used to categorise teams according to whether games have been closely contested or not (Gomez, Lorenzo, Sampaio, Ibanez & Ortega, 2008; Sampaio & Janiera, 2003; Ziv, Lidor & Arnon, 2010) but has had little use in PI research. This study will use both linear and logistic regression models and decision trees to assess their relative worth in providing meaningful, objective performance indicators for professional rugby league in the UK.

Methods

Sample

Data were provided in spreadsheets (Excel v2013, Microsoft Inc., Redmond, USA) by Opta from 567 matches played in the 27 rounds of the 2012, 2013 and 2014 European Super League seasons. These were extracted for analysis using Visual Basic for Applications in Microsoft Excel. To enable clear comparisons between winning and losing teams, draws (n=22) were excluded. Ethical approval was granted by a University Ethics Sub-Committee.

Form variables

The relative form differential between the home and away teams was assessed using 5 measures of form for each individual game. Five game form (points gained in the previous 5 games) was calculated using the home team's points minus the away team's. Similarly, current league form was calculated in the same way using total points gained during the season. Three further form measures used league position which meant that low values equated to higher form. Hence, end of current season league position, previous season league position and average of past 3 season's league position were calculated using the away team's score minus the home teams to ensure that all form values consistently attributed positive values to the home team having better form and negative values when the away team had better form.

Action variables

Relative (home minus away) frequencies for all action variables were used as the predictor variables. Field (2009, p.212) suggested a need for some rationale for the inclusion of variables into a regression analysis, if the correlation coefficient, in relation to point's difference, was >0.3 (a medium effect size; Cohen, 1992). Twenty-four variables were therefore selected: score first, plays, time in possession, total sets, completed sets, tackles, missed tackles, play the ball, quick play the ball, carries, metres gained, breaks, support carry, dominant carry, tackle bust, supported break, successful pass, unsuccessful pass, total passes, successful collections, first carry, first carry metres, scoot and scoot metres.

TABLE 1 NEAR HERE

Collinearity diagnostics were then performed to remove variables that had high multicollinearity i.e. tolerance values <1 and variance inflation factor (VIF) values >10

(Field, 2009). Variables that had multicollinearity issues such as plays (VIF= 125.24), total sets (VIF= 19.78), tackle busts (VIF= 116.70) and play the ball (VIF= 88.53) were removed as their variation could be better explained by other variables in the dataset, therefore leaving the relative frequency of 20 action variables for analysis.

Statistics

All data were analysed using IBM SPSS Statistics package (v21, IBM Corp., New York, USA). Backwards logistic and linear regression models, as recommended for sport performance research by Atkinson and Nevill (2001, p.817) were used on the 2012 and 2103 data. Standardized residuals were analysed to ensure no bias in the models (both deemed acceptable according to Field, 2009, p.293). VIF (<4.70) and Tolerance levels (>.21) did not indicate any collinearity issues (Field (2009, p.242). Cook's distances were analysed to ensure values were <1 (Field, 2009, p.293 and leverage and DFBeta values were <1 and indicated no cause for concern (Field, 2009, p.293). Cases having residual values >3 (Field, 2009, p.293) were investigated. Cross-validation, using the 2014 data (Field, 2009, p.222) assessed the fit of each model. An exhaustive CHAID decision tree was also grown using win/loss as the binary response variable.

Results

Logistic Regression

Backwards logistic regression removed the least important variables sequentially based on the likelihood-ratio for each variable (Field 2009, p.272) resulting in relative frequencies for 11 action variables in the final model, correctly classifying match outcome 91% of the time (Table 2). The model predicted that if the home team scored first the likelihood of winning was 74.4% (OR=2.91) whereas finishing the previous season one position lower than an opponent equated to a probability of winning of

44.0% (OR=0.88).

Table 2 near here

When the 2014 data was used to cross-validate the model using the 11 retained variables, match outcome was correctly classified 92.2% of the time.

Residual analysis

Four outliers were identified in the residual analysis (Table 3) and all incorrectly classified as home team losses. In each game, 5 (n=2) or 6 (n=2) variables contradicted the usual relationship with match outcome with the away team always gaining the most metres even though the home team won the game.

Table 3 near here

Linear Regression

A backwards stepwise linear regression removed the least important variables sequentially based on the significance value of the t-test statistic for each variable (Field 2009, p.213). The final model retained the relative frequencies for 10 action variables (Table 4) which explained 86.5% of the variation in points difference. If the effects of all other predictors were held constant (Field, 2009) then an additional completed set for the home team would be predicted to increase the points difference by 1.2 points.

Table 4 near here

Comparison of the regression models

Thirteen variables were identified as key performance indicators and three as performance indicators, a summary of both regression models can be seen in Table 5.

Table 5 near here

Exhaustive chi-square automatic interaction detection (CHAID) decision trees

A machine learning (data mining) technique was adopted to create a decision tree model that could best predict winning and losing from a training sample of 75% (85.4% accuracy; Figure 1), and cross-validated against a test sample of 25% of the data (85.5% accuracy). If relative metres gained values were not extreme i.e. <259 or >-258, the home team were 60.9% likely to win, this rose to 78% if they matched or outperformed their opposition on the number of completed sets but rose to 91.8% if the home team outperformed their opponents by 25 or more first carry metres,

Discussion

Mackenzie and Cushion (2013) identified a 'theory-practice gap', arguing that previous performance analysis research in soccer had a lack of transferability and that investigations had little or no relevance to practitioners in sport. They suggested that the aim of this type of research should be for practitioners to utilise the results to improve performance. Three statistical approaches were compared to determine KPIs that predicted either match outcome or points difference in rugby league. Match outcome (win or lose) had the advantage of simplicity, with the relatively uncommon draw, excluded as it did not distinguish good or bad performance. Points difference had the advantage of delineating performances on a linear ratio scale from very poor to very good. The two regression analyses provided concordant (5 common variables) and discordant (5 variables unique to each) results which were not straightforward to understand, particularly for coaches and players without statistical expertise. In contrast, the CHAID decision trees presented a simple, understandable message which lacked the, arguably, necessary detail to be practically informative.

Previous research indicated that scoring first could help increase a team's chances of winning in soccer (Garcia-Rubio, Gomez, Lago-Penas & Ibanez, 2015; Pratas, Volossovitch & Carita, 2016), hockey (Jones, 2009) and basketball (Courneya, 1990). However, as rugby league is a high scoring sport, it would be logical to assume that scoring first would not be as important a factor in determining whether a team won or lost as for low scoring sports. However, both regression results showed this variable to be the most important predictor, indicating that scoring first increased the chances of winning significantly. However, caution is necessary when interpreting this result as the odds ratio had confidence intervals between 1.2 and 7.1. Within a large sample of matches, there would be instances of matches won easily by a superior team who more often than not scored first and won (high odds ratio for scoring first resulting in a win i.e. 7.1, upper confidence limit). Conversely, there would be matches where two evenly matched teams could either score first and win or lose (odds ratio would be approximately 1 i.e. 50:50 chance). Assuming a fairly normal distribution, all other matches would be distributed between these two situations resulting in an overall average probability of scoring first resulting in a win of about 75%. This pretty much matches the result found (74.4%). It is therefore suggested that when interpreting a regression analysis the confidence limits should be considered, rather than the single beta coefficient or odds ratio, as these reflect the range of values evident within the data set.

The other concordant findings from the regression analyses could be categorised as relative measures of factors that could be labelled "form" (current season final league position), “amount of possession” (completed sets and metres gained) and “quick plays” (scoots i.e. a direct carry at the onset of a possession). Form has previously been shown to be an indicator of success in rugby league (league finishing position; Gabbett, 2014) although Carling, Wright, Nelson and Bradley (2014) suggested that the best measure of form might be the cumulative number of points gained at the time a game was played (identified as significant in the linear regression results). This study used five measures of relative form, which were proxy measures for the difference between the two teams in terms of quality. The results suggested that relative form did influence match outcome although the measures used here should only be considered as approximations of the true difference in team form. This is because many factors contribute to team form and are usually not accounted for e.g. absence of significant players, and others typically not available to researchers e.g. lack of motivation.

A team can only score if they have possession of the ball and an obvious predictor of scoring was therefore the amount of possession. However, having possession does not necessarily mean a team will score, as often happens in soccer. In rugby league if a team scores the next play requires the opposition to kick the ball back to the scoring team which implies that a winning team would have more possessions than the losing one. The relative frequencies of a number of action variables were highly correlated with time in possession, such as number of passes, carries, sets etc. This complicated the results as the regression methods used here removed variables that did not significantly add to the prediction of the dependent variable. This meant that many variables related to the amount of possession, and correlated highly with match outcome, were not included in the final model. For example, breaks was removed by the logistic regression despite previous research in rugby union (Diedrick and Van Rooyen, 2011) suggesting that 51% of tries resulted from breaks. However, the goal of the regression techniques used here, was to minimise the number of explanatory variables in a model. This had the advantage of being simple and could identify the most important variables from many, potentially less useful, ones. However, this reductionist method could also give a misleading account of which variables were important as the non-inclusion of breaks in the model exemplifies. One solution to this paradox could be the utilisation of a dimension reduction technique such as principal component analysis. This technique groups similar variables together into one component facilitating both the simplicity of reduced variables, whilst retaining the complexity of many variables.

The regression models agreed that scoots significantly predicted match outcomes. Whilst this variable may be associated with a quick play, it is an alternative to passing the ball at the outset of a possession, it is a relatively small aspect of performance but unrelated to variables associated to the amount of possession. Both models suggested that increasing the number of scoots reduced the probability of winning i.e. by inference passing the ball was the superior option. However, both models equated changes in the number of scoots to marginal differences in game outcome since the regression equation values relate to the probability of changing the outcome (match outcome or points difference) depending on the value of the predictor variable. So, a unit gain in scoots, or any other significant variables, may increase the probability of winning a match more for instances when a team had less scoots than the opposition compared to when they had gained more. In addition to this, the scale is not necessarily linear meaning that simple multiplication would lead to erroneous probability assessments. Taking all of this into consideration the simple probability assessments in relation to “if we improved this variable by one unit we would increase our chances of winning by this amount” only provide meaningful values for dichotomous variables such as scoring first. Scalar variables are far less interpretable even if you consider it sensible to ignore the fact that the probability values are associated with all other variables remaining unchanged, which in reality is unlikely.

The analysis of residuals from the logistic regression model highlighted performances which the regression model was unable to correctly predict. The four games incorrectly predicted as losses were due to unexpected performance on several variables. However, this was, perhaps, unsurprising given that teams can win, even if it is by just 1 point, when outperformed on many variables.

An analysis of possession in Australian professional rugby league found that possessions, following an opposition completed set, were least likely to end in a try (Kempton, Kennedy & Coutts, 2016). The decision tree analysis suggested that when teams were not unevenly matched on metres gained, outperforming the opponents on completed sets best increased the chance of success. However, both of these variables are “outcome” measures and don’t inform the processes undertaken successfully to enable these to happen (cf. James, 2009). For example, completed passes, carries, metres gained, play the ball, successful collections and breaks are variables that would likely lead to a completed set. From a coaching perspective, it is the processes that lead to successful outcomes that are important as these are the things that can be practised and improved. This suggests that if stepwise regression approaches are to be used, only process variables are used as predictors to avoid outcome measures being retained in the model.

Analysing multiple teams together, as in this study, may provide general rules regarding important aspects of the game, but as teams are likely to play with different tactical approaches different data gathering methods are needed to elicit these differences. For example, a team may be set up to play in a way that requires line breaks to be successful, whereas another team might focus on defensive variables. If it is the case that different teams do employ different strategies then putting lots of teams into one analysis, without categorizing appropriately, is bound to deemphasise the importance of a variable since it may only be important to some teams and not to others. This point highlights an important distinction between analyses using large data sets that allow complex analyses but do not inform about individual differences and smaller more focussed data sets that may not be valid for statistical analyses but provide rich qualitative information to inform the coaching process. This dichotomy is the paradox (theory-practice gap) highlighted by Mackenzie and Cushion (2013) and remains elusive.

Conclusion

An objective method for identifying KPIs and assessing their worth has been presented in this study using linear and logistic regression as well as decision trees. The results tended to focus on outcome variables related to keeping possession to gain metres. Whilst some process variables were identified as important e.g. successful passes and collections, the reductionist approach of these statistical techniques meant that meaningful performance indicators were removed from the final models. It was also apparent that the 'theory-practice gap' alluded to by Mackenzie and Cushion (2013) is a paradox that cannot be solved with large data sets unless more discriminating information relating to both process rather than outcome measures, and related to individual teams, is factored into the analyses. Future studies should investigate the suitability of using a dimension reduction technique e.g. principle component analysis, to identify the relationship between PIs and KPIs, in particular process variables, with a methodology that facilitates the identification of individual team differences.

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Table 1. Operational definitions of performance variables left in the final analyses.

Variables	Definition
Breaks	The ball carrier breaks the first line of defence
Completed Sets	Where the team in attack reaches their 5th tackle without losing possession of the ball, or scores a try
Dominant carry	The ball carrier gains a dominant position over the defender when engaging in contact
First carry	A carry to gain metres, there has been little attempt to do anything with possession other thant o gain territory
Metres gained	Metres gained are calculated from the gain line
Scoot	A carry directly from the play the ball, where no passes are involved
Score first	Whether the team scores the first try or not
Successful collections	A player has secured possession of the ball, when possession is not guaranteed. For example each catch from a pass does not count as a collection
Successful Pass	The pass went to, and was caught cleanly, by its intended target
Support Carry	A carry where the player has supported a previous ball carrier on the same phase of play
Supported Break	The ball carrier has supported a player making an initial break and received the ball continuing the attacking move
Time in possession	A possession is the period of time a team has full control of the ball from receiving the ball until the ball is turned over to the opposition
Total passes	A player has attempted to throw the ball with purpose to a team mate
Successful pass	The pass went to and was caught cleanly by its intended target
Unsuccessful pass	A pass that is intercepted by the opponent, gone forward or results in an error

Table 2

Table 2: Relative Performance indicators that best predicted match outcome (win/loss) in rugby league

Variables	**β (SE)**	**Odds Ratio**	**95% Confidence Interval**		**Probability**
			Lower	**Upper**	
(Constant)	-0.6 (0.4)	0.6			
Score First	1.1 (0.5)*	2.9	1.2	7.1	0.74
Completed Sets	0.5 (0.1)***	1.6	1.4	1.8	0.61
Current season final league position	0.2 (0.1)**	1.2	1.1	1.4	0.54
Successful Collections	0.1 (0.1)	1.1	1.0	1.2	0.52
Dominant Carry	0.1 (0.0)	1.1	1.0	1.2	0.52
Metres Gained	0.0 (0.0)***	1.0	1.0	1.0	0.50
Scoot Metres	0.0 (0.0)*	1.0	1.0	1.0	0.50
Time in Possession	0.0 (0.0)*	1.0	1.0	1.0	0.50
Successful Pass	0.0 (0.0)**	1.0	1.0	1.0	0.49
Scoot	-0.1 (0.0)**	0.9	0.8	1.0	0.45
Previous season final league position	-0.1 (0.1)*	0.9	0.8	1.0	0.44

Note: β is the unstandardized beta coefficient, SE is the standard error, *p<.05, **p<.01, ***p<.001. Probability is probability of winning (calculation for OR >1 = OR/(OR+1); OR <1 = OR/2).

Table 3: Outliers in Logistic regression model

	Exp.	Outlier 1	Outlier 2	Outlier 3	Outlier 4
Actual match outcome	Home win	Home win (1 pt)	Home win (16 pts)	Home win (4 pts)	Home win (1 pt)
LR predicted outcome	Home win	Away win	Away win	Away win	Away win
Previous season final league position	+	-13	-1	-5	-4
Current season final league position	-	-13	1	-7	-13
Score first	+	No	No	No	Yes
Possession (seconds)	-	65	-99	-328	334
Completed sets	+	4	-6	-4	5
Metres gained	+	-136	-63	-258	-64
Dominant carries	*	-12	2	-13	-15
Successful passes	-	10	-6	-17	60
Successful collections	*	5	-3	-5	-1
Scoots	-	1	-16	-20	4
Scoot metres	+	-50	-99	-114	20

Note: Exp. are the expected values (negative or positive) according to the logistic regression model.
* indicates that the Beta coefficient confidence intervals were not reliable.
Red indicates values inconsistent with actual match outcome

Table 4

Table 4: Relative performance indicators that best predicted points difference in rugby league.

	2012 & 2013 Dataset $R^2 = 0.865$			2014 Dataset $R^2 = 0.874$		
		Confidence Interval			**Confidence Interval**	
Variables	**β (SE)**	**Lower**	**Upper**	**β (SE)**	**Lower**	**Upper**
(Constant)	-0.9 (0.8)	-2.5	0.6	-1.2 (1.1)	-3.4	1.0
Score First	2.4 (1.1)*	0.4	4.5	3.7 (1.6)*	0.6	6.8
Completed Sets	1.2 (0.1)***	1.0	1.4	1.0 (0.1)***	0.7	1.2
Breaks	0.9 (0.2)***	0.6	1.3	0.9 (0.3)***	0.4	1.4
Current season final league position	0.6 (0.2)***	0.3	0.9	0.3 (0.2)	-0.2	0.7
Supported Breaks	0.4 (0.2)	-0.1	0.8	0.7 (0.4)	0.0	1.4
Unsuccessful pass	0.4 (0.1)**	0.1	0.6	0.2 (0.1)	-0.1	0.5
Metres Gained	0.0 (0.0)***	0.0	0.0	0.0 (0.0)***	0.0	0.0
Total passes	-0.1 (0.0)***	-0.1	-0.1	-0.1 (0.0)**	-0.1	0.0
Cumulative league form	-0.2 (0.1)*	-0.4	0.0	0.1 (0.1)	-0.1	0.4
Scoot	-0.2 (0.1)***	-0.3	-0.1	0.0 (0.1)	-0.2	0.1

Note: β is the unstandardized beta coefficient, SE is the standard error, *p<.05, **p<.01, ***p<.001.

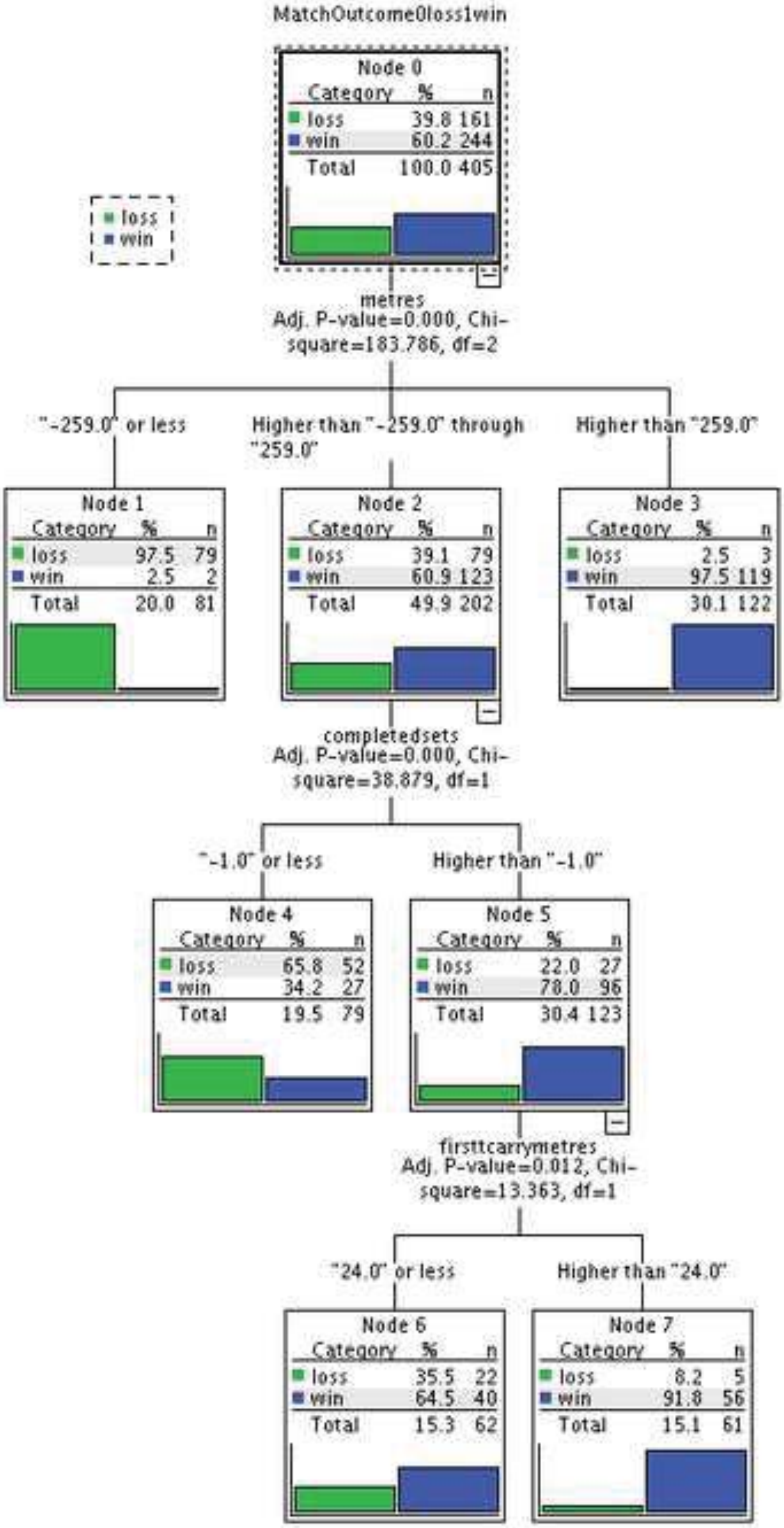
Table 5

Table 5. List of PIs and KPIs identified by the linear and logistic and their effects on success.

Variables	Logistic Backwards				Linear Backwards			PI/KPI
	Odds Ratio	Confidence Interval		Probability	β	Confidence Interval		
		Lower	Upper			Lower	Upper	
Score first	2.9	1.2	7.1	0.74	2.4	0.4	4.5	KPI
Completed Sets	1.6	1.4	1.8	0.61	1.2	1.0	1.4	KPI
Current season final league position	1.2	1.0	1.3	0.54	0.6	0.3	0.9	KPI
Successful collections	1.1	1.0	1.2	0.52				PI
Dominant carry	1.1	1.0	1.2	0.52				PI
Metres gained	1.0	1.0	1.0	0.50	0.0	0.0	0.0	KPI
Scoot metres	1.0	1.0	1.0	0.50				KPI
Time in possession	1.0	1.0	1.0	0.50				KPI
Successful Pass	1.0	1.0	1.0	0.49				KPI
Scoot	0.9	0.8	1.0	0.45	-0.2	-0.3	-0.1	KPI
Previous season final league position	0.9	0.8	1.0	0.44				KPI
Breaks					0.9	0.6	1.3	KPI
Supported Break					0.4	-0.1	0.8	PI
Unsuccessful pass					0.4	0.1	0.6	KPI
Total passes					-0.1	-0.1	-0.1	KPI
Cumulative league form					-0.2	-0.4	0.0	KPI

Note: β is the unstandardized beta coefficient. Probability is probability of winning (calculation for OR >1 = OR/(OR+1); OR <1 = OR/2).

Figure 1


MatchOutcome0loss1win
Node 0
Category % n
loss 39.8 161
win 60.2 244
Total 100.0 405
loss
win
metres
Adj. P-value=0.000, Chi-square=183.786, df=2
"-259.0" or less
Higher than "-259.0" through "259.0"
Higher than "259.0"
Node 1
Category % n
loss 97.5 79
win 2.5 2
Total 20.0 81
Node 2
Category % n
loss 39.1 79
win 60.9 123
Total 49.9 202
Node 3
Category % n
loss 2.5 3
win 97.5 119
Total 30.1 122
completedsets
Adj. P-value=0.000, Chi-square=38.879, df=1
"-1.0" or less
Higher than "-1.0"
Node 4
Category % n
loss 65.8 52
win 34.2 27
Total 19.5 79
Node 5
Category % n
loss 22.0 27
win 78.0 96
Total 30.4 123
firsttcarrymetres
Adj. P-value=0.012, Chi-square=13.363, df=1
"24.0" or less
Higher than "24.0"
Node 6
Category % n
loss 35.5 22
win 64.5 40
Total 15.3 62
Node 7
Category % n
loss 8.2 5
win 91.8 56
Total 15.1 61