

1           **Using principal component analysis to develop performance indicators**  
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3           **in professional rugby league**  
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# Using principal component analysis to develop performance indicators in professional rugby league

Previous research (Parmar et al., 2017) on performance indicators in rugby league has suggested that dimension reduction techniques should be utilised when analysing sporting datasets with a large number of variables. Forty-five rugby league team performance indicators, from all 27 rounds of the 2012, 2013 and 2014 European Super League seasons, collected by Opta, were reduced to 10 orthogonal principal components with standardised team scores produced for each component. Forced-entry logistic (match outcome) and linear (point's difference) regression models were used alongside exhaustive chi-square automatic interaction detection decision trees to determine how well each principle component predicted success. The ten principal components explained 81.8% of the variance in point's difference and classified match outcome correctly ~90% of the time. Results suggested that if a team increased 'amount of possession' and 'making quick ground' component scores, they were more likely to win ( $\beta=15.6$ , OR=10.1 and  $\beta=7.8$ , OR=13.3) respectively. Decision trees revealed that 'making quick ground' was an important predictor of match outcome followed by 'quick play' and 'amount of possession'. The use of PCA provided a useful guide on how teams can increase their chances of success by improving performances on a collection of variables, instead of analysing variables in isolation.

Keywords: rugby league; performance indicators; scoring performance; principal component analysis; regression.

## Introduction

Performance indicator research is important as it allows for sport performance to be measured empirically. It has been conducted in various sports such as soccer (Castellano and Casamichana & Lago, 2012; Jones, James & Mellalieu, 2004; Lago-Peñas, Lago-Ballesteros & Rey, 2011), rugby union (Bishop & Barnes, 2013; Hughes, Hughes, Williams, James, Vučković & Locke, 2012; Villarejo, Palao, Ortega, Gomez-Ruano & Kraak, 2015) and basketball (Csataljay, O'Donoghue, Hughes & Dancs, 2009;

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Gómez, Lorenzo, Ibañez & Sampaio, 2013; Puente, Coso & Salinero, 2015). However, few papers have analysed performance indicators in rugby league (Parmar, James, Hughes, Jones and Hearne, 2017; Woods, Leicht, Jones and Till, 2018; Woods, Sinclair & Robertson, 2017).

Within rugby league, Woods et al. (2017) analysed three hundred and seventy-six team observations taken from a publicly available statistics website, using thirteen team performance indicators to assess their effect on match outcome and final league position in the 2016 Australian National Rugby League (NRL) using ordinal regression and conditional interference classification decision trees. Try assists, all run metres, offloads, line breaks and dummy half runs were retained within the classification tree detecting 66% of the losses and 91% of the wins. However, the inclusion of variables such as try assists did not give meaningful information as this is simply a proxy for tries scored. Future performance indicator research should exclude variables that directly relate to scoring i.e. outcome variables, and rather, focus on the process variables (cf. James, 2009). Furthermore, the methods indicated that Woods et al. (2017) analysed team performances in isolation whereas better context could have been provided by making data relative to the opposition (cf. Hughes and Bartlett, 2002). However, the use of classification trees provided informative albeit simple results in regard to how performances on different variables could affect success depending on the range performed, which differs from regression models which only consider single unit increases of the predictor variables, this becomes problematic when analysing variables such as metres gained where teams sometimes perform several hundred more or less than their opponents.

Within the European Super League (ESL), Parmar et al. (2017) analysed five hundred and sixty-seven professional rugby league matches to determine how team

1 performance indicators predicted match outcome and point's difference. The authors  
2 excluded variables that related to scoring and made action variables relative by  
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4 subtracting the away team score from the home team's, therefore contextualising  
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6 performances and creating performance indicators (Hughes and Bartlett, 2002). A  
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8 combination of linear and logistic regression models alongside exhaustive chi-square  
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10 automatic interaction detection decision trees were utilised, with teams more likely to  
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12 win and gain more point's when they scored first and increased completed sets.  
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14 Conversely, teams decreased their chance of winning when they performed more scoots,  
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16 suggested as an inferior option compared to passing the ball.  
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21           Atkinson and Nevill (2001) recommended backwards elimination as the most  
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23 suitable regression method when analysing sport performance. This method removes  
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25 variables sequentially based on their contribution to the models' dependent variable  
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27 (e.g. match outcome). However, this comes with a reduction of predictive ability, albeit  
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29 generally small, at each step. Parmar et al. (2017) questioned the appropriateness of  
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31 stepwise methodologies when analysing sporting performance due to the removal of  
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33 variables that had previously been identified as important, and less frequently occurring  
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35 variables which could have a dramatic effect on a team's chances of winning (e.g.  
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37 yellow and red cards). They also suggested that dimension reduction techniques could  
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39 be useful for analysing large datasets that have many variables that are related to each  
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41 other, as variables that are explaining similar variance in the dataset would be grouped  
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43 together to form a component (cf. Bracewell, 2003; Parmar et al., 2017). However,  
44  
45 despite this, principal component analysis (PCA) has rarely been used in performance  
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47 analysis research. Rugby league performance is complex and multi-faceted and  
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49 consequently success can depend on performances on numerous variables which are  
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51 dependent on each other. Therefore, it is suggested that PCA can help produce more  
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1 relevant results, as it can explain that improving a set of correlated variables i.e. ball  
2 carries, metres and line breaks, can lead to a higher component score, and could lead to  
3 a better chance of success. Furthermore, the component scores can be calculated and run  
4 in a regression model to identify how well these components can predict the variation in  
5 success. This can provide coaches and analysts with more informative results to aid  
6 training and tactical methods, ultimately to improve team performances.  
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14 Mackenzie and Cushion (2013) discussed the ‘theory to practice gap’,  
15 suggesting that many papers lack relevance or usefulness to practitioners,  
16 recommending that future performance analysis research address this issue. PCA has  
17 been argued to be difficult for coaches to interpret (O’Donoghue, 2008) due to multiple  
18 variables being condensed into components, however, analysing variables  
19 independently of each other can also be misrepresentative as they can be related to  
20 performance on other variables. For example, Woods et al. (2017) found that line breaks  
21 could help determine whether a team won or lost a game. However, line breaks are  
22 related to other variables such as ball carries and metres gained. Therefore, presenting  
23 this variable in isolation is arguably more unrepresentative in terms of real-world  
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41 Therefore, this study used PCA to reduce team performance indicators into  
42 orthogonal components whilst also producing standardised scores of performance on  
43 each component per game. These component scores will then be assessed using non-  
44 stepwise methods due to the dataset already being reduced, hence forced-entry  
45 regression analysis and decision trees will be used.  
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## Methods

### *Sample*

Data were provided in spreadsheets (Excel v2016, Microsoft Inc., Redmond, USA) by Opta from 567 matches played in the 27 rounds of the 2012, 2013 and 2014 ESL seasons. These were extracted for analysis using Visual Basic for Applications in Microsoft Excel. 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 five measures of form for each individual game. Five game form (point's gained in the previous 5 games) was calculated using the home team's point's minus the away team's. Similarly, current league form was calculated in the same way using total point's gained during the season.

Three further form measures used league position (end of current season league position, previous season league position and average of past three season's league position ) and were calculated by subtracting the home team's league position from the away team's, hence positive values to the home team having better form and negative values when the away team had better form.

### *Performance indicators*

Forty-five action variables (as well as form variables) were made relative by subtracting the away team's performance from the home teams, therefore creating performance indicators (PIs). Hence positive values resulted when the home team outperformed the away and negative for the opposite. PIs that related to scoring were excluded from the analysis to provide more informative results.

## *Statistical Analyses*

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3 PCA with orthogonal rotation (varimax method), was used to better understand the  
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5 structure of the PIs and to reduce the dataset to a more manageable size to overcome  
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7 multicollinearity issues in regression using IBM SPSS Statistics package (v21, IBM  
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9 Corp., New York, USA). Component scores were saved using the Anderson-Rubin  
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11 method. After rotation, ten components (Figure 1), which explained 73.4% of the  
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13 variance were retained because of the large sample size and for having eigenvalues >1.  
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19 To enable a clear comparison of variables between winning and losing teams,  
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21 draws (n=22) were excluded. The principal component scores saved from the PCA was  
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23 run in both Linear (Point's difference) and Logistic (Win/Loss) forced entry regression  
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25 analyses using a data splitting method (Field, 2009) on a random selection of 75% of  
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27 the data. The models produced were then used to predict point's difference/match  
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29 outcome using the same variables for the remaining 25% data using Minitab (v17,  
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31 Minitab Inc., State College, PA). Crosstabs were performed to compare the predicted  
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33 probabilities produced by the model per game to the actual match outcome.  
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37 Probabilities were re-coded into winning probability (0.5-1) and losing probability (0-  
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39 0.49).  
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43 Standardized residuals were analysed to ensure no bias in the regression models,  
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45 if cases were within the recommended limits (Field, 2009, p.293). VIF ( $\leq 2.11$ ) were not  
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47 reported as there were no indications of collinearity issues (Field (2009). Cooks  
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49 distances were also analysed to ensure all values were <1 (Field, 2009) and only  
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51 reported if this assumption was violated.  
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56 An exhaustive chi-square automatic interaction detection (CHAID) decision tree  
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58 was grown using win/loss as the binary response variable in IBM SPSS Statistics package  
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60 (v21, IBM Corp., New York, USA) using a training (75%) and test (25%) sample.  
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## Results

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3 PCA was conducted on forty-five PIs with the contribution of PIs to the principle  
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5 component scores shown through the estimated correlations. If the PI had a positive  
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7 value, it improved the component score. Conversely, when the PI had a negative value,  
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9 for example missed tackles, the component score for making quick ground reduced.  
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FIGURE 1 NEAR HERE

### *Summary of Linear and Logistic forced entry regression models*

The ten principal components were entered into a linear regression without stepwise methods (Table 1) which explained 81.8% of the variance in point's difference. Of the four principal components forced into the model, increasing performance on 'attempting to continue the possession' (related to both successful and unsuccessful offloads) was predicted to reduce the number of point's gained marginally. Correlation coefficients were utilised to assess models predicted point's difference and actual point's difference for forced entry linear regression models.

The same principal components were then run in a forced entry Logistic regression (Table 1). With the non-significant variables included, the predictive model suggested that having a player sent off was not likely to make a significant change in the chance of winning i.e. a 47.2% change in the probability. Similarly, the model predicted that if a team improved their 'ratio of penalties gained to conceded' principal component score by one unit, assuming all other component scores remained the same, the chances of winning would improve by 55.7% (OR=1.3). The logistic regression



1 model was able to correctly classify wins 88.3% and 90.5% of the time on the training  
2 and test samples respectively.  
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7 **TABLE 1 NEAR HERE**  
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13 ***Residual analysis from the linear regression model***  
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16 One outlier was identified in the residual analysis ( $>3$ , Table 2). The regression model  
17 correctly identified the result as a home win, albeit by 11 point's as opposed to the  
18 actual 44 point's. In this match, two variables (amount of possession and quick plays)  
19 had values which were negative and counter to what was expected by the model.  
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21 However, the remaining four variables were consistent with the rest of the data and  
22 hence the model predicted the correct result.  
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37 ***Exhaustive CHAID Decision Tree (Machine Learning)***  
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40 A machine learning (data mining) technique was used to create a decision tree model to  
41 predict winning and losing (Figure 2) from a training sample of 75%, and cross-  
42 validated against a test sample of 25% of the data. The decision tree showed the most  
43 important principal components being making quick ground, followed by amount of  
44 possession and finally form.  
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55 **FIGURE 2 NEAR HERE**  
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1 The training sample was able to correctly classify 76.0% of games and the test-  
2 sample revealed that it could classify 78.8% of games correctly (Table 8).  
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## 6 **Discussion**

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9 The identification of variables that lead to success is an integral part of performance  
10 analysis. Coaches and athletes are constantly trying to understand how to improve  
11 performance, performance analysis aids this process particularly through attempting to  
12 provide a greater understanding of reliable PIs and KPIs. This investigation aimed to a)  
13 reduce the dataset whilst retaining as much of the variance as possible, using PCA, b)  
14 assess the suitability of the principal components in predicting match outcome (logistic  
15 regression and decision trees) and final point's difference (linear regression), c) provide  
16 results that are relevant and transferable for practitioners.  
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28 The PCA created ten principal components, which were grouped into four main  
29 categories, explaining 73.4% of the variation in the dataset. These were possession  
30 (41.1%), speed of play (20.9%), form (6.0%) and infringements (5.3%), with 26.4% of  
31 the variance not explained. The separation of possession and speed of play was an  
32 important distinction as rugby league is a territorial game, with teams having to score by  
33 moving the ball past their opponent's try line. Therefore, teams that can speed up their  
34 plays are thought to gain more metres as the defending team have less time to organise  
35 their defensive line adequately. The variable 'retaining possession following a kick'  
36 loaded onto 'speed of play' possibly because teams that were successful on the other  
37 speed variables were more successful at retaining possession following restarts,  
38 logically speed would play a part in this. Success on this variable can give a significant  
39 territorial advantage to a team and can easily be coached in terms of strategies to  
40 maximise the potential for retaining possession. Similarly, defensive quickness can  
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reduce the effectiveness of the opposition's attack ability and therefore contributes to the speed of play component group.

Amount of possession loaded highly ( $>0.6$ ) with metres gained and first carry metres and was clearly related to gaining metres. However, the principal component named "Making quick ground" loaded on variables associated with relatively dramatic, sudden increases or decreases in metres gained e.g. tackle busts, support carries, missed tackles and unsuccessful passes. These variables have the potential to make a significant impact on the outcome of a possession as evidenced through the regression and decision tree results, whilst also accounting for a large amount of variance in the dataset (20.9%) and as such are key factors for coaching interventions. In addition, unsuccessful passes were positively loaded onto this component. This is an unusual observation, however this could simply be a proxy for a team attempting risky plays or trying to keep the ball alive, which could give them a substantial advantage when performed successfully, but frequently result in unsuccessful passes. The other principal components that predicted significant amounts of variance were form (3a), quick plays (2c) and losing possession early (1b). The "form" component was a proxy measure for individual team differences which enabled the analysis to consider the differential in team qualities. However, the confidence intervals are more relevant to the understanding of association. The confidence intervals for form were 3.0 and 7.1 indicating that large differences in form i.e. large differences in team quality, were associated with high probabilities of wins for the better team whereas low positive differences associated with win probabilities were akin to home advantage.

The backwards logistic and linear regression parsimonious models both retained the same five principal components, with the linear regression model also including defensive quickness in its final model. This principal component consisted of one

1 positively loaded variable; 10m offside, where teams were caught offside at the 10m  
2 mark following a tackle, more times than the opponents. An explanation could be that  
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4 whilst defending, the team could have a strategy of sending more players in to the tackle  
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6 to dominate the attacking player and prevent a quick play the ball, therefore delaying  
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8 the defensive retreat to the referee. On the other hand, it could be due to the team having  
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10 a strategy of 'line speed' where the defending team attempt to leave the line quickly to  
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12 prevent the opposition from gaining metres, and in the process receiving a penalty  
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14 against them for leaving the defensive line prior to the ball being played by the  
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16 opponents.  
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22 The pairwise measures of association revealed a trivial reduction in predictive  
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24 ability when stepwise methods were utilised. This reduction of components provided an  
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26 easier 'take-away message' for practitioners, however the principal components that  
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28 were removed could be the difference between winning and losing in closely contested  
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30 matches, and therefore performances on these excluded components may give teams the  
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32 competitive edge to win. Butterworth, O'Donoghue and Cropley (2013) mentioned the  
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34 potential importance of minute 'performance gains' to winning and losing on occasions  
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36 in sport in their review of performance profiling literature, however this approach  
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38 gained significant media attention after GB Cycling attributed their 7 gold medals in the  
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40 2012 London Olympics to their 'marginal gains' philosophy (Slater, 2012). This is  
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42 where they aimed to improve every component of cycling by 1%, with the collective  
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44 improvements resulting in better performance overall. As such it would appear that  
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46 stepwise procedures are not practical for analysing complex sports as variables with  
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48 relatively low explanatory powers are removed whereas it is reasonable to believe that  
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50 these could make a significant difference to a match outcome, particularly in closely  
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52 contested matches. Sport is a dynamic and multi-faceted process where performance  
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1 depends on the interaction, usually reactive to the opposition, in both team and  
2 individual sports.  
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4           Decision trees were utilised to identify key performance indicators, which could  
5 be interpreted with ease by practitioners. Despite the transferability of results, the cross-  
6 validation revealed that their predictive ability was slightly lower than the regression  
7 methods. The component that explained the most amount of variance in the dataset was  
8 amount of possession, which described that improving the team's ability to retain  
9 possession of the ball is critical to increasing the probability of winning, which can be  
10 achieved by improving the associated variables. However, the decision trees indicated  
11 that making quick ground was the most important variable that could increase the home  
12 team's chances of winning to 72.7%, increasing to 91.6% when also increasing the  
13 amount of possession. However, large differences were evident in the confidence  
14 intervals (lower 7.0 and upper 22.8) for making quick ground, this could be attributed to  
15 the large variation between team qualities in the dataset. For example, top rated teams  
16 would be expected to make quick ground more than lower rated teams. Furthermore,  
17 each team would be expected to perform differently to each other as shown through the  
18 differences in confidence intervals. Therefore, future studies could consider creating  
19 nomothetic performance profiles to understand how performances on principal  
20 components generally differ according to team quality and idiographic profiles for a  
21 more informative understanding of individual team performances on principal  
22 components.  
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24           This study found that cumulative league form loaded the highest onto the form  
25 principal component, followed by final league position. This suggested that Carling,  
26 Wright, Nelson and Bradley's (2014) comments, which recommended the use of current  
27 form as a more appropriate and fairer method to assess team quality, were justified.  
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1 Future research into other sports should consider using this measure of team quality,  
2 and assess its suitability according to the sport analysed.  
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5 The use of PCA was suggested to be a better approach to analyse performance  
6 especially when utilising regression methods which suffer from multicollinearity issues,  
7 by forming orthogonal components comprised of related variables. The suitability of  
8 this decision was evident in the residual analysis as only one outlier was identified from  
9 the large sample size. This outlier highlighted that although the team had performed on  
10 5 components as expected, two components were unexpected (amount of possession  
11 and quick play) which led the model to predict a win by 11 point's, but which actually  
12 resulted in a winning difference of 44 point's. This case emphasised the fact that whilst  
13 sporting events can follow predictable patterns to some extent e.g. winning teams  
14 almost always gain more metres than their opponents and score more tries, large wins,  
15 as in this instance, can display unusual patterns in the data, probably due to unusual  
16 tactics which could be down to players sent off, player injuries (from either side) or  
17 poor playing conditions etc.  
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38 Future research should consider the inclusion of cumulative league form when  
39 assessing team quality, where appropriate. In addition, performances on KPIs and PIs  
40 should be assessed using performance profiling techniques to identify differences  
41 between teams. Furthermore, including the effects of independent variables when  
42 creating performance profiles is warranted, as this approach can help to provide  
43 informative results for practitioners, as this study identified large variations on some  
44 odds ratio confidence limits.  
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## 57 **Conclusion**

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59 This study identified a method that provided a more realistic guide on how teams could  
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1 increase their chances of success by improving performances on a collection of  
2 variables as opposed to traditional methods, which typically describe individual  
3 variables. Finally, decision trees provided an insight into how machine learning can be  
4 used to provide interpretable results for PCA when compared to the output from  
5 regression models, despite a reduced predictive ability. Future studies could compare  
6 performance on these KPIs and PIs using contextual ideographic performance profiles  
7 to provide a better understanding of the variation found within and between team  
8 performances on PIs and KPIs.  
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Table 1. Linear and Logistic regression models

Variable	Linear Regression			Logistic Regression			
	$\beta$ (SE)	$\beta$ 95% CI LB UB	$\beta$ (SE)	OR	OR 95% CI LB UB	Probability	
Constant	12.0 (0.5)	11.0 13.0	1.0 (0.2)				
Amount of possession (1a)***	15.6 (0.5)	14.6 16.6	2.3 (0.3)	10.1	5.7 18.0	0.91	
Making quick ground (2a)***	7.8 (0.5)	6.8 8.8	2.6 (0.3)	13.3	7.3 24.4	0.93	
Form (3a)***	-2.6 (0.5)	-3.5 -1.6	1.5 (0.2)	4.7	3.0 7.3	0.82	
Losing possession early (1b)***	5.1 (0.5)	4.1 6.1	-0.9 (0.2)	0.4	0.3 0.6	0.21	
Quick play (2c)***	-0.3 (0.5)	-1.4 0.7	1.2 (0.2)	3.4	2.3 5.1	0.78	
Attempt to continue the possession (1c)	0.7 (0.5)	-0.3 1.7	-0.3 (0.2)	0.8	0.5 1.1	0.39	
Ratio of penalties gained/conceded (4a)	-0.1 (0.5)	-1.2 0.9	0.2 (0.2)	1.3	0.9 1.8	0.56	
Retaining possession following a kick (2d)	1.9 (0.5)	0.9 2.9	-0.2 (0.2)	0.8	0.6 1.1	0.40	
Defensive quickness (2b)	-0.3 (0.5)	-1.3 0.6	0.2 (0.2)	1.2	0.9 1.7	0.55	
Player sent off (4b)	12.0 (0.5)	11.0 13.0	-0.1 (0.1)	0.9	0.7 1.3	0.47	
Dataset	R <sup>2</sup>	Pearson r with PD	Classification % Win	Classification % Loss			
Training	0.818	0.904***	88.3	83.7			
Test		0.908***	90.5	86.2			

Note:  $\beta$  is the unstandardized beta coefficient, SE is the standard error, OR is the odds ratio,  $\beta$  CI is the 95% confidence intervals for  $\beta$ , OR 95% CI is the 95% confidence intervals for the OR, LB is lower boundary of CI and UB is upper boundary of CI, PD is point's difference, \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ . Probability is probability of winning (calculation for  $OR > 1 = OR / (OR + 1)$ );  $OR < 1 = OR / 2$ ).

Table 2. Principal component scores and model predicted values for an outlier identified in residual analysis

<b>Case 245</b>	<b>Predicted</b>	<b>Outlier</b>
Match outcome	Win (11 pts)	Win (44 pts)
Making quick ground (2a)	+	1.2
Amount of possession (1a)	+	-0.8
Form (3a)	+	0.4
Quick play (2c)	+	-1.8
Defensive quickness (2b)	+	1.1
Losing possession early (1b)	-	-0.3

Note: Values in red signify the divergence between the outlier values and the regression model predicted values i.e. positive (+) or negative (-)

Figure 1

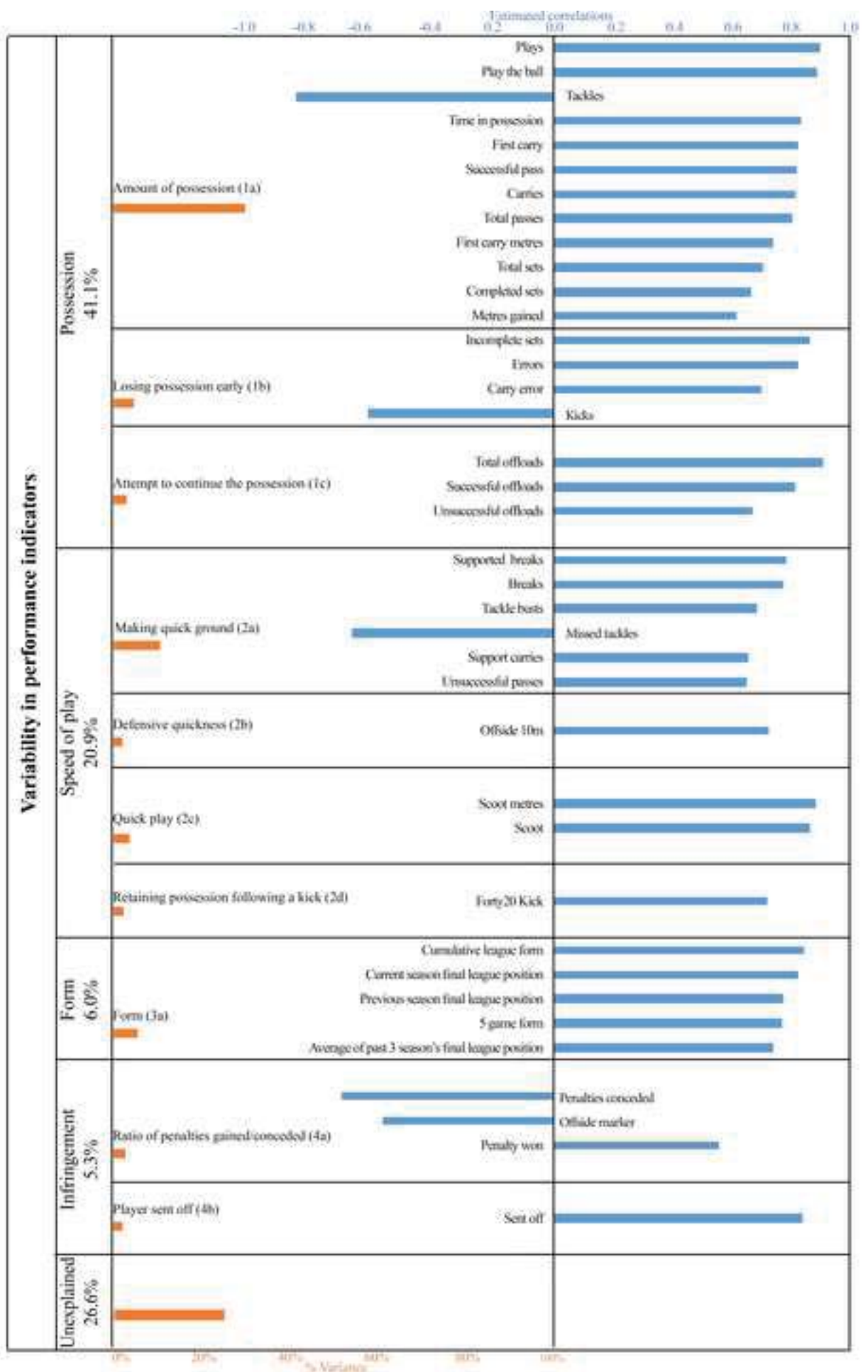


Figure 2

