DETERMINING, SCORING AND PRESENTING SUCCESSFUL PERFORMANCE IN PROFESSIONAL RUGBY LEAGUE

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT

Performance indicators allow for the objective quantification of performance (Vogelbein, Nopp & Hokelmann, 2014). However, limited PI research for professional rugby league exists, with just one paper published (Woods, Sinclair and Robertson, 2017) although this was conducted on teams from the Australian elite competition, the NRL, with no similar attempts for Europe’s Super League competition. Therefore, this thesis aimed to identify robust indicators of success for professional rugby league teams in super league, which would subsequently allow performances to be scored and assessed graphically through performance profiles.

Data from all 27 rounds of the 2012, 2013 and 2014 European Super League seasons were collected by Opta, amounting to 567 matches. Data for 45 action variables was extracted from spreadsheets using Visual Basic for Applications in Microsoft Excel (Excel, v2013, Microsoft Inc., Redmond, USA). To enable clear comparisons between winning and losing teams, draws (n=22) were excluded.

Study 1 assessed twenty-four relative variables (home value minus away) using backwards logistic (match outcome) and linear (points difference) regression models alongside exhaustive Chi-Square Automatic Interaction Detection (CHAID) decision trees to identify performance indicators (PIs) and key performance indicators (KPIs). However, some variables which were thought to be important (as identified by previous literature) were removed from the analysis as they did not contribute to the model’s predictive ability as much as others thus calling into question the appropriateness of stepwise methods. Furthermore, unusual results were evident which lead to the conclusion that a suitable dimension reduction technique could be more appropriate to analyse large datasets with multiple variables that could be related to each other.

Study 2 utilised principal component analysis to reduce 45 action variables into 10 orthogonal principle components. These components were analysed using backwards and enter methods in logistic and linear regression models alongside CHAID decision trees. This method provided a relevant guide on how teams could improve their performance by improving a collection of variables as opposed to traditional methods which described individual variables. Furthermore, the use of stepwise methods was argued to be less appropriate for sporting performances as some principal components that could relate to success may be removed. Results from both regression models indicated large variations on confidence intervals for beta coefficients and odds ratios, suggesting that the variation of a set of values are more representative of the data analysed, when assessing multiple teams. Therefore, idiographic assessments of performances were suggested to provide relevant information for practitioners, which can be lost through traditional nomothetic approaches, as evidenced in this study.

Study 3 utilised the principle component scores to create idiographic performance profiles, according to match venue and match closeness. In addition, a case study was produced assessing two teams' previous performances, prior to an upcoming game, providing a practical example of how practitioners could utilise this information in their respective environments. Although large variations were evident on profiles, it was suggested that team performances may never stabilise due to the unpredictability of complex sports involving multiple players like rugby league. However it was clear that idiographic profiles provided meaningful and informative assessments of performance which were arguably more relevant for practitioners compared to traditional nomothetic methods.

Overall, this thesis facilitated a greater understanding of how rugby league teams perform in Super League, through the use of practical and relevant methodologies that can be utilised by practitioners and coaches who are constantly striving to improve sporting performance. Future research must consider the ‘theory-practice’ gap identified by McKenzie and Cushion (2013) in order to provide simple and relevant answers that practitioners require, which seems to be a principle that has remained elusive thus far.

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I would like to dedicate this PhD to my late Father. I was only able to take on this challenge through his financial support and backing. He had picked up extra hours to cover my tuition fees up until I was awarded a fully funded studentship in 2013. Sadly, he suddenly passed away a year later in 2014. He was a very kind and loving father and selflessly supported our family. His selfless dedication to supporting me embark on this journey has certainly carried me through every challenging moment since.

I would like to express appreciation and gratitude to my Mother. She has been my source of inspiration and strength, setting the standard for myself and my brothers, having excelled academically as an Advanced Skills Teacher, Head Teacher and finally now an Education Consultant. She was awarded a Fellowship in Religious Education through Oxford University, despite raising three children and enduring many personal adversities, she has managed to have a successful career. She has guided us through many fun and tough challenges and the completion of this PhD would not have been possible without her continued emotional and financial support.

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5. Parmar, N., James, N., Greenhalgh, A. and Hughes, M.D. (2014). Developing team performance indicators in professional rugby league. Research paper presented at the 10th World Congress of Performance Analysis of Sport; Opatija, Croatia, September. In Goran Sporiš, Zoran Milanović, Mike Hughes, Dario Škegro (Eds.), Book of Abstracts of the 10th World Congress of Performance Analysis of Sport; Opatija, Croatia, September, pp.118.

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Figure 0.1. Infographic showing outline of thesis and brief overview of chapters.

CHAPTER 1: INTRODUCTION

1.1 THE EVOLUTION OF PERFORMANCE ANALYSIS

Performance analysis (PA) has emerged as a discipline within sports science over the last 30 years. It has developed from early notation techniques (using symbols, numbers or letters) for quantifying and recording actions taking place in a sporting event. Early techniques can be traced back to dance (Laban, 1948), baseball (Fullerton, 1912) and basketball (Messersmith and Corey, 1931). The goal for these people was simple, to analyse their sport, often using quite rudimentary techniques such as frequency counts and cross tabulations, to answer simple questions such as "who has the best passing statistics?" or who should I select in this particular position?". In the UK and Europe, probably the most influential, and certainly the most controversial, notational analyst was Charles Reep, who died in 2002 (Pollard, 2002) having devoted over 50 years to analysing football (and other sports) in great detail. In the mid-1970s Liverpool Polytechnic (now Liverpool John Moores University) started the first sports degree, independent of Physical Education, and some of their researchers had dramatic impacts on the future of Performance Analysis as a discipline within its own right. Reilly and Thomas (1976) coded football players' movements into standing, walking, trotting, running and sprinting categories. This relatively simple analysis had profound consequences as football coaches were able to match training schedules to actual match demands for the first time. Similarly, Sanderson and Way (1977) adapted Jake Downey's (1973) notation system for tennis to pioneer the analysis of squash. Mike Hughes, a squash coach and lecturer, developed undergraduate academic courses in PA, and, along with a multitude of students, notation systems for a wide range of sports, including squash. Whilst much of this work was unpublished, or published within proceedings of conferences, the impact of Mike's work was profound. He continued to develop academic courses and saw their popularity increase exponentially. He also approached sports teams and National Governing Bodies to provide notational analysis support, something almost unheard of in the early 1980s. As a consequence of the success of these ventures he decided to promote Performance Analysis, most notably notational analysis, by instigating the International Society of Performance Analysis of Sport in 1992 (formerly known as the International Society of Notational Analysis) and later the International Journal of Performance Analysis in Sport in 2001. By founding these two important outlets for academic work in Performance Analysis, Mike led the rapid growth in this area. His influence today reaches across the world and the large expansion of academics in this area has seen a similar rise in publications, both textbooks and research papers, published in a wide range of high impact International journals.

As interest in PA grew, companies started to produce specialist software whilst sports teams began employing performance analysts (starting around the mid 1980's). In 2017 almost all professional football clubs employ specialist performance analysts with the biggest teams having around 15 full time staff in this capacity. Similarly, most major sports, including rugby union and to a lesser degree rugby league, have full time performance analysts working alongside coaches to help deliver feedback to players. The role of these analysts usually consists of measuring and record actions (notational analysis) and the movements of players with a view to describing the events either during or after the match has finished. Varying degrees of complexity and precision are possible with technology playing a major role in how PA is developing. Consequently, PA can be seen as both an academic discipline and an applied support service although the goals for both can sometimes merge. However, Mackenzie and Cushion (2013), in their review of performance analysis research in soccer, identified a 'theory-practice gap', arguing that much performance analysis research in soccer had little or no relevance to practitioners in sport. It is perhaps ironic then, that whilst the analyses undertaken in performance analysis have become complex and sophisticated, the original goal of understanding sport better to answer simple questions may have been forgotten, at least by some academics.

1.2 PERFORMANCE ANALYSIS OF PROFESSIONAL RUGBY LEAGUE

Rugby league coverage has increased over the past few years with more leagues from the UK, Europe and Australia covered. Despite this, performance analysis has not been widely adopted in the sport, with many clubs not employing a full-time analyst. In the same way, there is a gap for performance analysis research to be conducted on rugby leagues top-flight competition in the northern hemisphere, with one paper analysing the Australian NRL competition (Woods, Sinclair & Robertson, 2017) and one on elite youth rugby league (Cupple & O'Connor, 2011). However, Opta collect a large array of performance variables from each super league game, with the in-depth analysis provided to each Super league team and the national governing body, the Rugby Football League.

Established over 20 years ago (1996), Opta are a world-leading provider of in-depth sports data, both live and post-match. Over 800 clients in approximately 40 countries use their data. Typical clients include broadcasters, digital publishers, bookmakers, national governing bodies, national teams, professional sports teams and athletes to name a few. Television broadcasters typically use statistics from sporting data to engage their viewers and to try and provide an objective analysis (Worsfield et al., 2009), companies like BBC and Sky Sports regularly use data from companies like Opta for their coverage of sports matches. Furthermore, Wright et al. (2013) found that 70.2% of analysts working within professional football use data provided by an external company, like Opta, to provide or supplement their team and player analysis, with the number of teams estimated to increase since the paper was published.

Reliability of sport performance data has been widely discussed (Hopkins, 2000; Hughes et al., 2004; James et al., 2007, O'Donoghue, 2007; Tenga et al., 2009; Worsfield et al. 2009; Liu et al., 2013; Sykes et al. 2013; Waldron et al., 2014). James et al. (2007, p.2) defined reliability in performance analysis as "the extent to which the event codes reflect what happened in the game". Performance analysis data should be valid and reliable to ensure meaningful generalisations can be made (Hughes & Bartlett, 2002; Glazier, 2010; Liu, Hopkins, Gomez and Moulinuevo, 2013).

Therefore, an appraisal of Opta's methods was conducted and presented below to determine if the methodologies employed by the company to collect rugby league data could be considered reliable.

1.3 EVALUATION OF OPTA'S DATA COLLECTION METHODS

A critical evaluation of Opta's data collection methodology was undertaken. A visit to Opta's leeds offices was undertaken in Early 2013.

1.3.1 RECRUITMENT AND TRAINING

Opta look for analysts with outstanding knowledge of rugby league, good ICT skills and preferably with performance analysis experience. Once suitable analysts have been selected, they are subject to a rigorous training programme including:

- Rules and player knowledge test
- Operational definition training
- Live coding test – analysts must meet 95% accuracy on Opta analysis system

If candidates excel in the training programme, they are then invited to complete an advanced training programme.

1.3.2 OPERATIONAL DEFINITIONS

A comprehensive 21-page definition handbook has been developed by Opta in conjunction with professional Super League coaching staff and the Rugby Football League. All rugby league analysis is conducted with these operational definitions to enable reliable and robust measures of performance to be collected. These definitions are reviewed and revised subject to changes on future rules changes. A summary of key variables definitions is provided below (full definitions can :

Break:	The ball carrier breaks the first line of defense.
Carry	Player touching the ball has deemed to make a carry if they have made an obvious attempt to go forward and attack the opposition with the ball in hand.
Completed set:	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.
Errors:	A player has made an error which leads to the opposition gaining possession of the ball, either in open play or in the form of a scrum/lineout.
First carry:	A carry to gain metres, there has been little attempt to do anything with possession other than to gain territory.
Forty twenty kick:	The ball has been kicked from within the attacking team's 40 metre area and has bounced into touch in the opposition's 20 metre area.
Goal kicks:	A player has attempted to score points by kicking the ball.
Kicks:	A player has attempted to strike the ball with their foot.

Metres: Metres gained are calculated from the gain line.

Missed tackle: A tackle is deemed missed when a player has failed to affect a tackle on an opposition player when they were in a reasonable position to make the tackle.

Offload: The ball carrier has passed the ball in the process of being tackled.

Offside 10m: A defending player has failed to retire 10 metres from the play the ball or as encroached on the 10 metres before the ball has been played.

Passes: A player has attempted to throw the ball with purpose to a team mate.

Penalties: When a player or team has been deemed to be breaking the laws of the game by the referee, where a free kick or penalty is the appropriate sanction.

Play the ball: After a tackle is complete the attacker attempts to regain his feet place the ball on the ground and roll the ball between his legs with his foot.

Plays: The amount of chances a team has had in attack with the ball.

Quick PTB: The attacking player has been able to play the ball before the markers or the defensive line has set properly

Scoot: A carry directly from the play the ball, where no passes are involved.

Scoot metres: Metres gained from scoots (measured from the gain line).

Succ. 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 offload: The ball carrier has offloaded the ball straight into the hands of their own player.

Successful pass: The pass went to and was caught cleanly by its intended target.

Supported break: The ball carrier has supported a player making an initial break and received the ball continuing the attacking move.

Tackle: A player has attempted to halt the progress or dispossess an opponent in possession of the ball.

Unsuccessful offload: The ball carrier has offloaded the ball, which has been collected by the opposition.

Unsuccessful pass: A pass that is intercepted by the opponent, gone forward or results in an error.

1.3.3 MONITORING AND EVALUATION OF DATA

Once the analysts have completed coding a game, their data is subject to validation and reliability checks before being published, including:

- Tries, Conversions, Penalties and Cards
- 10 minute section of the game is analysed for accuracy
- Weekly analyst data check
- Monthly analyst data check

1.3.4 ANALYST EVALUATION

If an analyst does not meet the required accuracy standards then they must undertake the training process until they reach the 95% accuracy marker.

1.3.5 SUMMARY

It was deemed that the data collection and reliability methods demonstrated by the company was appropriate for maintaining quality data that is regularly checked.

1.4 AIMS AND OBJECTIVES

The aims of this thesis were:

- **Determine** which variables were best related to winning performance and therefore defined as performance indicators.
- Create orthogonal principal components to create standardised **scores** of team performances.
- **Present** principle component scores using idiographic profiles of team performances.

The objectives of this thesis were:

1. Review the existing performance indicator research from all sports and identify suitable methodologies for use in this thesis.

2. Create clear and suitable definitions of how action variables, performance indicators (PIs) and key performance indicators (KPIs) can be determined from performance variables.

3. Provide relevant and useful methodologies and results that can be utilised by practitioners and coaches to improve performance.

4. Identify reliable and robust performance indicators and key performance indicators through appropriate statistical analysis to understand what variables are important for winning/losing.

5. Identify a suitable statistical method to score team performances on performance variables (i.e. action variables, PIs and KPIs) to understand how teams have performed compared to each other.

6. Produce graphical assessments of performance using form charts and radar graphs (performance profiles) using suitable methodologies to provide a visual depiction of team performances allowing for comparisons to be made.

7. Utilise independent variables like match venue, team and opposition quality and match closeness to provide context to data, as suggested by previous research.

8. Contribute a better understanding of rugby league (European Super League) through the identification of performance indicators, scoring performances and creating profiles through relevant methodologies that can be applied to sport as a whole.

CHAPTER 2: REVIEW OF LITERATURE

2.1 INTRODUCTION TO LITERATURE REVIEW

Performance analysis (PA) is mainly used as a tool for understanding and improving sporting performance (Hughes & Bartlett, 2002) including rugby league (Gabbett, 2005) which, nevertheless, has been relatively under researched. Consequently, this review will consider methodologies and findings from a variety of sports in order to develop new methodologies for analysing individual and team rugby league performance.

Individual and team rugby league performance can be recorded as individual player actions such as each time a player carries the ball or makes a tackle. These actions are referred to as action variables and when analysed in the context of all actions in a match can be used to determine performance measures. Research has suggested that some action variables are more indicative of successful performance than others i.e. performance indicators (e.g. Hughes and Bartlett, 2002), whilst other research has looked at performance over a number of matches i.e. performance profiling (e.g. James, Mellalieu & Jones, 2005; O'Donoghue, 2005). Recently research has used multiple performances to try to predict future performance (e.g. Harrop and Nevill, 2014) or rating performances against some benchmark (e.g. Bracewell, 2003; Jones, James & Mellalieu, 2008). Each of these methodological approaches will be considered with respect to the statistical approach used, operational definitions for categorising actions, sampling techniques and the use of independent variables such as match location, form, and team and opposition quality. This critical review will conclude with suggestions for the studies in this thesis.

Summary information from the research reviewed in this thesis will be presented in Table format for performance indicators (Table 2.2), profiling (Table 2.4) and predicting and rating (Table 2.5). Each Table includes the full reference, sample size, statistics and reliability reported, summary of main findings and conclusions, and finally, limitations and suggestions for future research reported.

2.2 METHODOLOGY

Original and review journal articles were retrieved from electronic searches of Google Scholar and Web of Knowledge databases. Key terms used were 'performance indicators', 'winning sport performance', performance profiling', 'performance profiles', 'prediction sport' and 'rating sport'. Finally, using the relevant articles, reference lists and "cited by" were checked for additional articles that were suitable for the literature review and had not been identified through the database searches. Full list of articles used can be seen in Table 2.2 – 2.4.

2.3 PERFORMANCE INDICATORS/WINNING PERFORMANCE

2.3.1 INTRODUCTION

Performance indicators (PIs) have been defined as "…a selection, or combination, of action variables that aims to define some or all aspects of a performance" (Hughes and Bartlett, 2002, p.739). Hughes and Bartlett (2002) also suggested that for PIs to be useful they should relate to successful performance or outcome. PIs were categorised as match descriptors, biomechanical, technical or tactical variables but noted that some PIs could overlap between categories. Three key points related to presenting PIs were also made, 1) PIs should be used comparatively and not in isolation e.g. in relation to past, peer or opponent's performances. 2) Context should be provided so that end-users are not misled about a performance e.g. a shot per possession ratio provides better information about the ability to create shots than shots alone. 3) Information could be lost by ratios suggesting the use of non-dimensional data on occasion i.e. two identical ratios could hide the fact that one team performed more actions than the other.

Team and opposition quality has been found to be an important independent variable when analysing performances (Castellano & Casamichana, 2015; Jones et al., 2004; Lago, 2009; Lago-Penas & Dellal, 2010; Lago-Penas, Lago-Ballesteros & Rey, 2011; Taylor et al, 2008; Vogelbein et al., 2014). This has typically been defined as the analysed team's final league position from the previous season with teams then categorised as strong, weak, top 10 etc. However, Carling, Wright, Nelson and Bradley (2014) suggested that this method could be considered arbitrary and even unfair as teams could, for example, miss out on being classified as a strong team by just a few points, despite potentially having been in the top half of the Table for the majority of the season. The authors consequently recommended that future papers analyse team quality based on the league ranking at the time a match was played. It was suggested that this would make a quality variable more indicative of a team's performance throughout the season. Whilst this suggestion is logical, a number of different quality measures could be developed for future studies. Potential measures include 1) Recent form as assessed by performance over the past 5 games, 2) Season form measured by the total points gained from the beginning of season, 3) Previous form using the previous season's league position, and 4) Historical form which is the average league position from the past three seasons.

The reviewed PI research (Table 2.2) has involved a variety of sports with only two in rugby league (Cupples & O'Connor, 2011) who analysed individual positions for elite youth teams. They used a qualitative approach, the Delphi method, to develop PIs using a combination of an interview and two questionnaires completed by thirteen elite youth rugby league coaches in Australia. Common PIs across positions were suggested to be communication, mental toughness, reading the play, decision making and, to a lesser extent, some game based skills. This fairly subjective methodology may have been affected by personal bias due to the small sample size, future studies could therefore include more quantitative methods involving larger samples. The second being Woods, Sinclair & Robertson (2017) who utilised action variables from the National Rugby League website to try and explain match outcome and ladder position in the 2016 NRL season. CI classification trees classified losses correctly 66% of the time and wins 91% of the time using only five variables; try assists, all run metres, line breaks, dummy half runs (scoots) and offloads. Cumulative link mixed models (ordered regression) revealed a significant negative relationship between missed tackles and ladder position i.e. the lower you finish in the league the more missed tackles you will have. Furthermore, a significant negative relationship was observed for kick metres and dummy half runs with ladder position, with the lower frequency counts for both when finishing lower in the league. However, action variables were named as performance indicators without being shown to be related to success, perhaps the authors could have named the five variables left in the classification trees as performance indicators. Secondly, better context could have been provided, Hughes and Bartlett (2002) argued that variables should not be presented in isolation. Perhaps, further studies could benefit from making the data relative to the opposition or including further independent variables to provide more context and meaningful information to the reader.

Mackenzie and Cushion (2013) suggested that limited advances had been made within Soccer PA research, commenting that research had typically presented performances in overly descriptive and simplistic ways, with papers typically using a reductionist approach, with a particular focus on trying to establish relationships between performance variables and match outcome without providing sufficient context to the variables, contrary to Hughes and Bartlett's (2002) advice. However, examples to the contrary of this exist both in soccer (e.g. Taylor, Mellalieu, James & Barter, 2010) and other sports like basketball (e.g. Gomez, Lorenzo, Ortega, Sampaio & Ibanez, 2013) with more recent research utilising complex statistical procedures such as self-organising maps (Croft, Lamb & Middlemas, 2015) and chi-square automatic interaction trees (Gomez, Moral & Lago-Penas, 2015; Robertson, Back & Bartlett, 2016) although the effectiveness of these methods compared to widely used methods have not been analysed.

The sample size will have an effect on the statistics used, for example Field (2009) recommended that 10-15 cases of data per predictor should be available in order to use regression analysis. Similarly, there must also be enough data to make meaningful comparisons between independent variable categories e.g. team quality: top, middle and bottom teams, match location: home and away etc. This could be a reason why some papers have excluded or limited the use of independent variables in their methods. Therefore, PI research should utilise a large enough sample size in relation to the number of independent variables (IVs) and more importantly the number of levels for each IV.

2.3.2 SAMPLE SIZE

The PI research included in this review indicated that 56% of papers used less than 100 matches and 44% used more than 100 matches as their sample size. Mackenzie and Cushion (2013) found that only 22% of general soccer performance analysis (PA) research included samples of 100 games or more. Whilst the PI results is clearly an improvement over PA research in soccer, it is not clear why 56% of papers used less than 100 matches as their sample. Authors must consider how representative their samples are in respect to the particular sport, for example in the UK rugby union competitions play 132 matches at league stages, rugby league 189 and soccer 380. Some papers from this review have used less than 20 matches as their sample (Bishop & Barnes, 2013; Courel, Suarez, Ortega, Pinar & Cardenas, 2013; Gomez, Moral & Lago-Penas, 2015; Scholes & Shafizadeh, 2014; Prim, van Rooyen & Lambert, 2006). Therefore, future studies must address this issue to ensure their studies provide a true reflection of the sport and or competition analysed. Prim, van Rooyen and Lambert (2006) used a low amount of matches for their study, analysing just 9 games from the 2005 super 12 rugby union competition. Possession and duration of time in possession were analysed using ANOVA tests, with the remaining data analysed using Kruskal-Wallis tests. The use of such a small sample size suggests that the data is unlikely to be representative of the analysed teams' performances over the season, therefore generalisations about the competition or sport as a whole would be hard to make as discussed by previous research (Mackenzie & Cushion, 2013). In contrast, Robertson, Back and Bartlett (2016) identified PIs that explained match outcome in elite Australian Rules football. Three hundred and ninety six games were analysed using logistic regression to identify PIs that had significant relationships with match outcome e.g. whether a team won or lost, in addition chi-square automatic interaction detection classification trees (CHAID) were used to assess the relationship of the same indicators with match outcome, both using the 2013 data. CHAID has not been widely used in PA research until recently (see Gomez, Moral & Penas, 2015) and have been suggested to be easier for non-analysts to interpret. All models were then fitted to the 2014 data to assess the validity of the models. This approach to identify PIs could have been improved by using a clear structure of definitions for PIs as outlined in the introduction, this would have resulted in more meaningful information for coaching staff and performance analysts. For example identifying PIs more strongly related to success (KPIs) enables the readers of the paper to see which PIs are associated more with success when compared to other PIs.

2.3.3 INDEPENDENT VARIABLES

Independent variables help to put context to performance analysis data especially in PI research (Hughes & Bartlett, 2002). For example, scoring first can significantly increase the chances of winning in hockey (Jones, 2009), basketball (Courneya, 1990), and soccer (Garcia-Rubio, Gomez, Lago-Penas and Ibanez, 2015; Pratas, Volossovitch & Carita, 2016). Furthermore, when playing at home teams are more likely to win their games in volleyball (Alexandros, Panagiotis & Miltiades, 2012) and soccer (Garcia-Rubio, Gomez, Lago-Penas & Ibanez, 2015). Additionally, team quality has related to success in soccer (Castellano & Casamichana, 2015) and opposition quality has been shown to influence possession in soccer (Lago, 2009). Finally, match status (whether a team was winning, drawing or losing at the time a variable was measured) has been shown to affect possession in soccer (Jones et al., 2004).

Mackenzie and Cushion (2013) found that 55% of PA research in soccer included limited independent variables other than match outcome. This can also be seen in PI research included in this review, for instance, Najdan, Robins and Glazier (2014) identified PI's in English Twenty20 cricket. Whilst some important information was gained in terms of differentiating performances on action variables for both the winning and losing teams, more meaningful information could have been gained by accounting for independent variables. Another consideration for research could be to consider ways in which to differentiate winning and losing performances more meaningfully compared to whether a team simply won or lost. A better approach may be to use the final points difference of the match as the dependent variable to allow the identification of variables that lead to a greater points difference and those that lead to a lower points difference.

In addition, further context could be added for PIs, for example. whether PIs had differed according to whether teams were playing at home or away and when playing against top or bottom quality teams. Other papers have included selected independent variables whilst excluding some, for example, Castellano and Casamichana (2015) compared performances from 320 first division and 335 second division Spanish soccer matches, categorised as being either top or bottom quality of their respective leagues. However, they failed to account for opposition quality and match location despite previous papers (Jones et al., 2004; Lago, 2009; Lago-Penas & Dellal, 2010; Lago-Penas, Lago-Ballesteros & Rey, 2011; Taylor et al, 2008; Vogelbein et al., 2014) providing this context.

Jones, James and Mellalieu (2004) analysed possession in soccer according to match status and team quality. Twenty four matches from the 2001-2002 English Premier League season were analysed with each team having between 201 and 262 possessions per game amounting to 5580 possessions. However, possessions less than 3 seconds were excluded as these were not deemed to be indicative of a team's strategy but rather considered as random events e.g. tackles and goalkeeper clearances ($p=0.393$), leaving 3544 possessions for analysis. Results indicated that successful teams had significantly longer possessions than their opponents ($p<0.001$) regardless of match status but both successful and unsuccessful teams had longer possessions when they were losing compared to when winning ($p<0.05$). Finally successful teams kept possession longer (~10% were above 20 seconds) than unsuccessful teams (~4% were above 20 seconds; p<0.001) when winning. However, the effects of match location and opposition quality were not considered, both of which could have provided better context. Lago (2009) included match location, opposition quality and match status for possession length in 27 matches of a professional Spanish soccer team. Linear regression revealed that the interaction between match location and opposition quality accounted for 53% of the variation in possession. Furthermore winning teams had more possession when losing (p<0.01) but when teams played stronger opposition they had less time in possession (p<0.01). A limitation of this paper is that the results may only be indicative of the strategies and tactics employed by the analysed team and may not be indicative of other soccer teams' performance.

Vogelbein, Nopp & Hokelmann (2014) adopted a different approach to presenting ball possession by analysing the amount of time it took for teams to recover ball possession, which is, of course, the time of the opponent's possession. They argued that previous research had only focused on time in possession and neglected the time taken to recover ball possession when defending. The critical difference between these approaches is the method of data sampling. Jones et al. (2004) did not distinguish opponent quality when presenting time in possession (see retain possession row, Table 2.1). Vogelbein et al. (2014) however, did not distinguish the quality of the team in possession when presenting the time to regain possession (see regain possession column, Table 2.1). Results found that all teams required the most time to recover the ball when winning, agreeing with previous research (Jones et al., 2004 & Lago, 2009) which identified that losing teams had more time in possession. However, top teams recovered ball possession significantly quicker than bottom teams (p<0.001). Top teams recovered ball possession much quicker (~10 seconds) than in between and bot-

Table 2.1: Data collection method for sorting time of possessions for retaining and regaining possession according to team quality and match status

			Team in possession									
			Top team (*T*)			Middle team (*M*)			Bottom team (*B*)			
			Winning (*W*)	Drawing (*D*)	Losing (*L*)	Winning (*W*)	Drawing (*D*)	Losing (*L*)	Winning (*W*)	Drawing (*D*)	Losing (*L*)	Regain possession
Opponent	Top team	Winning			t_{TL}			t_{ML}			t_{BL}	$t_{TL} + t_{ML} + t_{BL}$
		Drawing		t_{TD}			t_{MD}			t_{BD}		$t_{TD} + t_{MD} + t_{BD}$
		Losing	t_{TW}			t_{MW}			t_{BW}			$t_{TW} + t_{MW} + t_{BW}$
	Middle team	Winning			t_{TL}			t_{ML}			t_{BL}	$t_{TL} + t_{ML} + t_{BL}$
		Drawing		t_{TD}			t_{MD}			t_{BD}		$t_{TD} + t_{MD} + t_{BD}$
		Losing	t_{TW}			t_{MW}			t_{BW}			$t_{TW} + t_{MW} + t_{BW}$
	Bottom team	Winning			t_{TL}			t_{ML}			t_{BL}	$t_{TL} + t_{ML} + t_{BL}$
		Drawing		t_{TD}			t_{MD}			t_{BD}		$t_{TD} + t_{MD} + t_{BD}$
		Losing	t_{TW}			t_{MW}			t_{BW}			$t_{TW} + t_{MW} + t_{BW}$
	Retain possession		$\sum t_{TW}$	$\sum t_{TD}$	$\sum t_{TL}$	$\sum t_{MW}$	$\sum t_{MD}$	$\sum t_{ML}$	$\sum t_{BW}$	$\sum t_{BD}$	$\sum t_{BL}$	

Key: t is time of possession, $\sum$ is sum

-tom teams, especially when drawing and losing. This agrees with previous research (Lago, 2009) which suggested that teams had less time in possession when they played stronger opponents. Jones et al. (2004) found that successful teams kept possession longer than unsuccessful teams ($p<0.001$) when winning. Hence more informative results would have been achieved if either study had included both team and opposition quality

This section of the literature review has demonstrated the need for independent variables to be included in PI research to allow for context and meaningful information to be gained. It is therefore important for authors to decide which independent variables are appropriate for inclusion in any investigation. For example, Gomez, Moral and Lago-Penas (2015) identified a lack of independent variables as a limitation in their study, and suggested that match status and competition stage may have been beneficial to include in their analysis. In some instances including too many independent variables increases the complexity of the analysis and subsequent results. This could be a reason why some papers have excluded them. However, where appropriate these should be included to give better context and more meaningful information not only for academic papers but for transferability to the applied world. By making the results focused around meaningful information for coaches and performance analysts, the 'theory-practice' gap (Mackenzie & Cushion, 2013) may be reduced.

2.3.3.1 OVERVIEW OF INDEPENDENT VARIABLES IDENTIFIED

Below is an overview of independent variables identified in this section that could provide relevant and meaningful context:

- Points difference (home minus away)
- Score first (Yes/No)

- Match status (Winning, Drawing or Losing)
- Match venue (Home/Away)
- Team and/or opposition quality (Top, Middle or Bottom or league position at time of match)
- Match closeness (Unbalanced/Balanced games)

2.3.4 DATA FROM INTERNATIONAL COMPETITIONS

Data from international competitions typically contain varying levels of teams according to the stage of the particular competition, therefore the differences between the stages of the competition and the quality of the teams in each stage should be accounted for. However, many papers do not account for this, for example Higham, Hopkins, Pyne and Anson (2014c) identified variables that differentiated between winning and losing teams, and the variables that led to success based on rankings and match outcome. Three hundred and ninety two matches from nine international men's tournaments from the 2011/2012 IRB Sevens World Series were analysed. Action variables related to scoring such as tries scored were excluded from analysis. Although the information gained from this study can give important information to coaches and teams who are preparing for international events, it lacked context which could have added more meaningful information to the results, for example including certain independent variables such as competition stage to see whether teams played differently according to the stage of the competition, team and opposition quality and whether a team played at home or away (match location) etc. Liu, Gomez, Lago-Penas and Sampaio (2015) analysed action variables that led to winning in the group stages of the 2014 FIFA world cup. Forty-eight matches from the group stages were included for analysis, with action variables being grouped according to whether they related to goal scoring, passing or defending. A k-means cluster analysis was used to identify close games (n=38) and unbalanced games (n=10), this seems an appropriate objective method to classify the games based on the final score, and gives a clear indication whether teams were evenly matched or not, similar to previous research (Csataljay, O'Donoghue, Hughes, & Dancs, 2009; Higham, Hopkins, Pyne & Anson, 2014c). Generalised linear regression was then used to identify PIs for close games and then all games. The strength of this paper was that it accounted for the separate stages of the competition, thereby enabling comparisons to be made on how teams had played according to the particular stage of the competition the match was played in. Furthermore, the identification of close and unbalanced matches show whether teams were evenly matched or not, perhaps team and opposition quality could also be included to give a more detailed and contextual analysis of performance. A final consideration is the use of two different competitions in a sample, Gomez, Perez, Molik, Szyman and Sampaio (2014) investigated elite men's and women's wheelchair basketball performance from 154 matches during the 2010 World Championship and 2008 Beijing Paralympic games, using discriminant analysis to identify the game related statistics that discriminated between winning and losing teams and linear regression to identify if the quality of opposition had an effect on the final points differential. Close (balanced) and unbalanced games were identified using similar methods to Liu, Gomez, Lago-Penas and Sampaio (2015). Authors should justify or account for the use of two different competitions for the sample as team and players and therefore strategies and tactics may differ according to the competition (Liu, Gomez, Lago-Penas & Sampaio, 2015). Therefore, studies should analyse competitions separately to avoid losing important information and make the results applicable to the particular competition analysed. However, the inclusion of points-differential as the dependent variable allowed more meaningful information to be gained on each action variable e.g. how they affected the final point's difference of the match, as opposed to whether a team just won or lost as this doesn't account for the point's difference which could have been small or large. E.g. whether a team won by 2 points or 20 points.

Due to the nature of international competitions, performance profiles (collection of action variables & PIs to represent team/individual performances) are hard to construct from limited sample sizes. Furthermore, international competitions have teams comprised of varying levels of quality, which can also be seen in their respective squads. Therefore the use of independent variables can help account for these variations to an extent. However, it is worth noting that the quality of competing teams can vary according to the particular sport analysed. One transferable part of research occasionally used for international competitions and demonstrated in part by Liu, Gomez, Lago-Penas and Sampaio (2015) is the importance of the particular stage of the competition. In relation to domestic competitions, this could be translated to looking at performances according to the first half of the season and second half of the season where teams fight for their finishing league positions and therefore it would be logical to assume that performances may differ according to the period of the season the game was played in.

Table 2.2. Performance indicator literature

#	Reference list	Sample	Reliability and Statistical Procedures	Main findings and Conclusion	Limitations reported	Suggestions for future research
1	Abraldes, J., Ferragut, C., Rodriguez, N. & Vila, M. (2012) 'Tactical and shooting variables that determine win or loss in top-Level in water polo', *International Journal of Performance Analysis in Sport*, 12(3), pp. 373-384.	*Matches*: 50 *Competition:* 2008 Euro Champs. 2009 World Champs *Sport*: Water Polo	*Reliability:* Kappa Index of Cohen *Intra*:>92% *Inter*: >87% *Statistics:* Kruskal-Wallis ANOVA	• Significant differences between winning and losing teams were found in coefficients of: • Euro Champs: Shot accuracy • World Champs: definition, resolution of shots and the resolution, detention and error of shots at goal		In-depth analysis of speed shots of teams at higher and lower classifications is recommended.
2	Ayán, C., Cancela, J. & Fernández, B. (2014) 'Changes in Wheelchair Basketball Performance Indicators throughout a Regular Season: a pilot study', *International Journal of Performance Analysis in Sport*, 14(3), pp. 852-865.	*Matches*: 12 players *Competition*: Spanish National First Division *Sport*: Wheelchair Basketball	*Reliability*: n/a *Statistics*: ANOVA	• Changes observed through the season in skills and fitness were mostly trivial with the exception of passing skills • Motor skills and fitness levels of elite Wheelchair basketball players do not experience much change through the season	WB skills and fitness levels were not available Not all playing classifications were covered	Future research should analyse several teams and cover all functional classification levels
3	Bishop, L. & Barnes, A. (2013) 'Performance indicators that discriminate winning and losing in the knockout stages of the 2011 Rugby World Cup',	*Matches*: 16 *Competition:* 2011 Rugby World Cup *Sport:* Rugby Union	*Reliability:* Percentage error test *Intra:* <5% *Inter: <3%*	• Winning teams kicked the ball out of their hand more and conceded less penalties in their half • Territory strategy through kicking/pressure is more effective than possession		Identify performance indicators across other competitions both domestic and international.

	International Journal of Performance Analysis in Sport, 13(1), pp. 149-159.		<u>*Statistics*</u>*:* Wilcoxon Signed Rank		
4	Bremner, S., Robinson, G. & Williams, M. (2013) 'A Retrospective Evaluation of Team Performance Indicators in Rugby Union', *International Journal of Performance Analysis in Sport*, 13(2), pp. 461-473.	<u>*Matches*</u>: 65 (1 team) <u>*Competition*</u>: Premiership Rugby <u>*Sport*</u>: Rugby union	<u>*Reliability*</u>: Cohen's Kappa <u>*Intra*</u>: N/A <u>*Inter*</u>: 0.65-1.00 <u>*Statistics*</u>: Logistic Regression	• Quick ruck, territory, and gain line had positive effects on match outcome • Slow ruck, turnovers, lost ruck and contact turnovers all had negative effects on match outcome. • Post-hoc confirmation provides a framework for assessment of PI's in PA	Analyse tackling technique
5	Campos, F., Stanganélli, L., Campos, L., Pasquarelli, B. & Gómez, M. (2014) 'Performance indicators analysis at Brazilian and Italian women's volleyball leagues according to game location, game outcome, and set number', *Perceptual & Motor Skills*, 118(2), pp. 347-361.	<u>*Matches*</u>: 132 & 108 (240) <u>*Competition*</u>: 2011-2012 Brazilian and Italian Women's League <u>*Sport*</u>: Volleyball	<u>*Reliability*</u>: N/A <u>*Statistics*</u>: Shapiro-Wilks ANOVA Mauchly test Greenhouse-Geisser Bonferroni post-hoc tests Effect sizes	• Home teams won 58% (Brazilian) and 56% (Italiant) of the time • Winning teams performed better on attack, block, serve and opponents error for games with 3 sets. On the 4th set opponents errors was also included. • Attack was the performance indicator most linked to winning and losing	Address different ages and levels of athletes Analysis of the sequence of actions within the rally
6	Carroll, R. (2013) 'Team performance indicators in Gaelic Football and Opposition Effects', *International Journal of Performance Analysis of Sport*, 13(3), pp. 703-715.	<u>*Matches*</u>: 57 <u>*Competition*</u>: 2011 & 2012 All-Ireland Senior Football Championship	<u>*Reliability*</u>: Percentage error test <u>*Intra*</u>: <5% <u>*Inter*</u>: <5% <u>*Statistics*</u>: Wilcoxon signed ranks tests	• Attack Efficiency %, Total Shots and % Opposition Kickouts Won were significant when comparing top against bottom teams • Fouls Committed and Total Goals were significant when comparing bottom teams with top teams • Opposition strength affected performance of top and bottom teams differently	Score-line effect on performance indicators Classification of Shots, Kickouts & Fouls

		Sport: Gaelic Football	Mann Whitney U tests			
7	Castellano, J. & Casamichana, D. (2015) 'What are the differences between first and second divisions of Spanish football teams?', *International Journal of Performance Analysis in Sport*, 15(1), pp. 135-146.	*Matches*: 42 *Competition*: 2013-2014 Spanish Football First and Second League *Sport*: Soccer	*Reliability*: n/a *Statistics*: ANOVA 1 way ANOVA 2 way Bonferroni	• Significant differences were found for all indicators with the top 10 teams in Spanish first league performing better • Bottom 10 teams in Spanish first league performed better than the top 10 teams in the second league	Use of means do not reflect game dynamics and variability Did not take into account independent variables	Identify indicators to evaluate player and team performance
8	Castellano, J., Casamichana, D. & Lago, C. (2012) 'The Use of Match Statistics that Discriminate Between Successful and Unsuccessful Soccer Teams', *Journal of Human Kinetics*, 31, pp. 139-147.	*Matches*: 177 *Competition*: World Cup (2002, 2006 & 2010) *Sport*: Soccer	*Reliability*: *Intra*: N/A *Inter*: 0.93-0.97 *Statistics*: Levene's test ANOVA Structural Co-efficient	• Variables that differentiated between winning, drawing and losing teams were total shots, shots on target and ball possession in attack and total shots received in defence. • Info may be of benefit to both coaches and player.		To consider shots received by the opposing team as a defence-related variable.
9	Courel, J., Ortega Toro, E., Cárdenas, D., Suárez, E. & Piñar, M. (2013) 'Is the inside pass a performance indicator? Observational analysis of elite basketball teams', *Revista de*	*Matches*: 9 *Competition*: 2012 Euro league Playoff *Sport*: Basketball	*Reliability*: Cohen's Kappa (intra) Multirater K (inter) *Intra*:>0.90 *Inter*: >0.84	• Inside pass should be considered a performance indicator • Successful inside pass occurs more frequently on passer location and immediate receiver action		Analyse the offense continuity through sequential analysis.

	Psicología del Deporte, 22(1), pp. 191-194		<u>*Statistics*</u>: Mann-Whitney U Chi-square Logistic regression			
10	Croft, H., Lamb, P. & Middlemas, S. (2015) 'The application of self-organising maps to performance analysis data in rugby union', *International Journal of Performance Analysis in Sport*, 15(3), pp. 1037-1046.	<u>*Matches*</u>: 76 <u>*Competition*</u>: NZ ITM Cup <u>*Sport:*</u> Rugby union	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Self-organising maps	• Self-organising maps help to identify types of matches in rugby union • Two styles consistent with winning was identified. • Two styles were consistent for losing teams • This methods highlights some advantages of SOM compared to stats mainly the identification of multiple styles of play and indicators to match outcomes.	May be difficult for coaches and practitioners to grasp	Build bespoke models based on coach/team/sport Determine map location couplings between teams.
11	Csataljay, G., O'Donoghue, P., Hughes, M. & Dancs, H. (2009) 'Performance indicators that distinguish winning and losing teams in basketball', *International Journal of Performance Analysis in Sport*, 9(1), pp. 60-66.	<u>*Matches*</u>: 54 <u>*Competition*</u>: 2007 European Basketball Championship <u>*Sport*</u>: Basketball	<u>*Reliability*</u>: N/A <u>*Intra*</u>: N/A <u>*Inter*</u>: N/A <u>*Statistics*</u>: Cluster analysis Wilcoxon Signed Rank Tests	• 13 significant performance indicators from the full set of matches • 6 critical from closely contested matches • Closely contested matches showed that winning teams had significantly less 3 point attempts with higher shooting percentage. • Number of successful free throws and the free throw percentage and the number of defensive rebounds also linked to success.		Use larger sample size
12	Cupples, B. & O'Connor, D. (2011) 'The Development of Position-Specific Performance Indicators in Elite Youth Rugby League:	<u>*Matches*</u>: 13 Elite Youth Coaches <u>*Competition*</u>:	Qualitative Research Delphi Method	• Results have helped to define positional indicators according to their influence • Cognitive indicators were found to have the most influence over positions,		Rationalising and validating why certain indicators were ranked important and

	A Coach's Perspective', *International Journal of Sports Science and Coaching*, 6(1), pp. 125-142.	National Youth Competition *Sport*: Rugby League	Mean and Frequency Distribution	followed by game skills and physiological indicators • Coaches at development levels should focus on cognitive and game skills	others not, would further the position-specific evaluation.
13	Drikos, S. & Vagenas, G. (2011) 'Multivariate assessment of selected performance indicators in relation to the type and result of a typical set in Men's Elite Volleyball', *International Journal of Performance Analysis in Sport*, 11(1), pp. 85-95.	*Matches*: 350 team performances *Competition*: 2009 Men's European Volleyball Championship *Sport*: Volleyball	*Reliability*: ICC Tests *Intra*: *Inter*: >0.90 *Statistics*: 1) MANOVA 2) Stepwise Discriminant Analysis	• Significant multivariate differences in type of set, in type of results, and in their interaction • Effectiveness of attack is the most important performance indicator for all types of sets • Training of a men's volleyball team should emphasize more to improve offensive abilities	Determine hierarchy of variables which can increase the % of correct discriminant classification Investigate the relationship between performance and randomness in the variation of the result
14	García, J., Ibáñez, S., Martinez De Santos, R., Leite, N. & Sampaio, J. (2013) 'Identifying Basketball Performance Indicators in Regular Season and Playoff Games', *Journal of Human Kinetics*, 36(1), pp. 161-168.	*Matches*: 323 *Competition*: 2007-2008 ACB Spanish League *Sport*: Basketball	*Reliability*: N/A Kappa = .92 of agreement of variables (no reliability test carried out) *Statistics*: Cluster of K-means ANOVA	• Winning teams dominated in assists, defensive rebounds, successful 2 and 3 point field goals during regular season games. • In play-off games the winning teams performed higher numbers of defensive rebounds.	Qualitative analysis can be performed to help give additional info not explained by quantitative analysis.

			Discriminant analysis		
15	García-Rubio, J., Gómez, M., Lago-Peñas, C. & Ibáñez, S. (2015) ‘Effect of match venue, scoring first and quality of opposition on match outcome in the UEFA Champions League’, *International Journal of Performance Analysis in Sport*, 15(2), pp. 527-539.	<u>*Matches*</u>: 475 <u>*Competition*</u>: 2009 to 2013 UEFA Champions League <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Linear Regression Logistic regression	• Home teams that score first win 62.3% of matches in group stages, this decreases to 55.8% in knockout stages. • Away teams have better winning % when not scoring first • Linear regression explained 30% of variation • Match location, scoring first and quality of opposition has effect according to stage of competition	Replicate current study whilst accounting for team tactics and playing styles.
16	Garganta, J. (2009) ‘Trends of tactical performance analysis in team sports: bridging the gap between research, training and competition’, *Revista Portuguesa de Ciências do Desporto*, 9(1), pp. 81-89.	<u>*Qualitative*</u>	<u>*n/a*</u>	• Tactical modelling can help identify match features and events according to offensive and defensive play • Individual actions in a game can destabilise or re-stabilise the game (system) • It is important to analyse the interaction between teammates and opponents • Hybrid models may allow for better modelling	Develop concepts and methods that allow game complexity and dynamic interaction to be analysed
17	Gómez, M., Lorenzo, A., Ibañez, S. & Sampaio, J. (2013) ‘Ball possession effectiveness in men's and women's elite basketball according to situational variables in different game periods’, *Journal of Sports*	<u>*Matches*</u>: 40 (7234 ball possessions) <u>*Competition*</u>: 2006-2007 Spanish Pro Men’s and	<u>*Reliability*</u>: Weighted Kappa <u>*Intra*</u>: 0.84-0.95 <u>*Inter*</u>: 0.80-0.91 <u>*Statistics*</u>: Binary Logistic Regression	• Men’s basketball performance indicators dependent on game period • Women’s basketball performance indicators dependent on situation variables (league stage and match status)/ • Match status was related to effectiveness only during the last 5 minutes of women’s games.	n/a

	Sciences, 31(14), pp. 1578-1587.	Women's League *Sport*: Basketball	Odds Ratio Confidence Intervals			
18	Gómez, M., Lorenzo, A., Ortega, E., Sampaio, J. & Ibáñez, S. (2009) 'Game related statistics discriminating between starters and nonstarters players in Women's National Basketball Association League (WNBA)', *Journal of Sports Science and Medicine*, 8(2), pp. 278-283.	*Matches*: 216 *Competition*: 2005 Womens WNBA League *Sport*: Basketball	*Reliability*: N/A *Statistics*: Discriminant analysis (Multivariate)	• Best teams had higher successful 2-point field goals, successful free-throws, fouls, assists and defensive rebounds when winning • Worst teams had higher successful 2-point field goals, successful free throws, assists and steals when winning. • Successful 2-point field goals, successful free throws and assists were the performance indicators that discriminated between players that started matches and those that did not start.		n/a
19	Gomez, M., Moral, J. & Lago-Penas, C. (2015) 'Multivariate analysis of ball possessions effectiveness in elite futsal', *Journal of Sports Sciences*, 33(20), pp. 2173-2181.	*Matches*: 9 *Competition*: 2012-2013 Spanish mens pro league *Sport:* Futsal	*Reliability*: Kappa *Intra*: >0.81 *Inter*: >0.78 *Statistics*: Logistic Regression Chi-Square Automatic Interaction Detection CHAID	• Results found that ending in goalkeeper's area and half court defensive pressure with effectiveness were related to successful ball possessions • Individual defence, set play and 0-3 passes were found to be related to unsuccessful ball possessions • This approach allows for trends to be identified by coaches and therefore improve strategies.	Did not take into account situational variables (competition stage and match status)	Offensive and defensive tactical systems, group-tactical behaviours and passing and shooting techniques should be further studied

20	Gómez, M., Pérez, J., Molik, B., Szyman, R. & Sampaio, J. (2014) 'Performance analysis of elite men's and women's wheelchair basketball teams', *Journal of Sports Sciences*, 32(11), pp. 1066-1075.	*Matches*: 78 & 76 *Competition*: 2010 World Championship and 2008 Beijing Paralympic Games *Sport*: Wheelchair Basketball	*Reliability*: *Inter*: ICC= 0.96 *Statistics*: Discriminant analysis Linear regression	• For balanced and unbalanced games, winning teams had more successful 2-point field-goals, successful free-throws, assists, steals, fouls received and defensive rebounds, whereas losing teams had more unsuccessful free-throws. • For unbalanced games, winning teams blocked more shots, secured more offensive rebounds and were fouled more. Losing teams had more turnovers and unsuccessful 3-point field-goals and committed more fouls.	Investigate wheelchair basketball according to player body type, positioning in chair, and ability to manoeuvre the chair around a defender.
21	Higham, D., Hopkins, W., Pyne, D. & Anson, J. (2014a) 'Patterns of play associated with success in international rugby sevens', *International Journal of Performance Analysis in Sport*, 14(1), pp. 111-122.	*Matches*: n/a 12 core teams summary stats and annual rankings *Competition*:2008/2009 to 2011/2012 IRB Sevens World Series *Sport*: Rugby 7s	*Reliability*: *Statistics:* Mixed model analysis Intra class coefficients Linear mixed model	• To improve team IRB rankings – teams should increase ball retention in line-outs and at the breakdown, turning the ball over more frequently in opposition rucks and by kicking fewer contesTable restarts.	Identify additional performance indicators associated with success
22	Higham, D., Hopkins, W., Pyne, D. & Anson, J. (2014b) 'Performance Indicators Related to Points Scoring and Winning in International Rugby Sevens', *Journal of Sports*	*Matches*: 196 *Competition*:2011/2012 IRB Sevens World Series *Sport*: Rugby 7's	*Reliability*: n/a *Statistics*: Intra class coefficients Mixed model analysis	• Teams that have greater ball possession, fewer rucks, mauls, turnovers, penalties and free kicks, and limited passing have a higher likelihood of winning. • Successful teams have better control of ball possession	Apply these techniques to other sports

	Science & Medicine, 13(2), pp. 358-364.		Generalised linear model Logistic regression			
23	Higham, D., Hopkins, W., Pyne, D. & Anson, J. (2014c) ‘Relationships between rugby sevens performance indicators and international tournament outcomes’, *Journal of Quantitative Analysis in Sports*, 10(1), pp. 81-87.	<u>*Matches*</u>: 392 <u>*Competition*</u>:2011/2012 IRB Sevens World Series <u>*Sport*</u>: Rugby 7’s	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Linear Mixed Modeling	• Teams that performed more entries in the oppositions 22m zone per match, tries per entry into the oppositions 22m zone, tackles per match, passes per match, rucks per match and a higher percentage of tackle completion had better mean rankings.		Investigate competition outcomes and tactical patterns of play
24	Hughes, M., & Bartlett, R. (2002) ‘The use of performance indicators in performance analysis’, *Journal of Sports Sciences*, 20(10), pp. 739-754.	<u>*Qualitative*</u>	<u>*n/a*</u>	• Performance indicators can be broken down into 4 main areas: Match descriptors, Biomechanical, technical and tactical indicators. • Data should be put into context either through comparisons and or the use of ratios where appropriate.	•	• Future research should utilise the guidelines provided in the study for each type of performance indicator
25	Hughes, M. T., Hughes, M. D., Williams, J., James, N., Vučković, G. & Locke, D. (2012) ‘Performance indicators in rugby union’, *Journal of Human Sport and Exercise*, 7(7), pp. 383-401.	<u>*Matches*</u>: Unclear <u>*Competition*</u>: 2011 Rugby World Cup <u>*Sport*</u>: Rugby Union	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: n/a??	• Points scored per match, points scored per match against tier a teams and tries scored per match all give information about performance of teams • Anomalies in data – such as runners up of tournament (France) had the least line breaks and tries per match. • Simple analysis of frequencies are not sufficient, for complex dynamic sports like rugby and as such context should be added.	•	• Qualitative studies needed of individual skill sets for each position • Use methods based on momentum, perturbations and sociometric network analysis.

26	Hughes, M. & Franks, I. (2005) 'Analysis of passing sequences, shots and goals in soccer'. *Journal of Sports Sciences*, 23(5), pp. 509-514.	*Matches*: 116 (52&64) *Competition*: 1990 & 1994 FIFA World Cup *Sport*: Soccer	*Reliability*: Percentage Agreement *Intra*: *Inter*: >99% *Statistics*: Linear regression	• 80% and 77% of goals were scored from four passes or less in the 1990 &1994 World Cups respectively. • Shots to goal ratio is better for direct play than possession play • Successful teams in 1990 world cup had better conversion of possession to shots on goal.	•	• Analyse more data • Establish amount of data is sufficient for profiling
27	Ibáñez, S., Sampaio, J., Feu, S., Lorenzo, A., Gómez, M. & Ortega, E. (2008) 'Basketball game-related statistics that discriminate between teams' season-long success', *European Journal of Sport Science*, 8(6), pp. 369-372.	*Matches*: 870 *Competition*: 2000-2001 to 2005-2006 Spanish Basketball League LEB1 *Sport*: Basketball	*Reliability*: n/a *Statistics*: 1 Way ANOVA Discriminant analysis	• Best teams perform significantly more successful free throws, defensive rebounds, assists, steals, blocks and offensive efficiency and significantly fewer fouls committed • Discriminant analysis revealed that best teams outperformed opponents on assists, steals and blocks.	•	• N/a
28	James, N., & Rees, G. (2008) 'Approach shot accuracy as a performance indicator for US PGA Tour golf professionals', *International Journal of Sports Science and Coaching*, 3(1), pp.145-160.	*Matches*: 14 players *Competition*: PGA Tournaments *Sport*: Golf	*Reliability*: % error *Inter*: 0.18% for starting distance and 0.07% for finishing distance *Statistics*: Central Tendency and Dispersion Spearman's rho correlation coefficients	• Shot accuracy is suggested as a viable performance indicator as it was strongly correlated with World Ranking • For skewed data median is better measure for the average as it better reflects the typical performance. • Literature suggests that driving distance has increased by about 30 yards and driving accuracy by 8%.	• Lack of ability to assess the lie of the ball • Lack of accurate measurement of the prevailing wind • Inability to know if a player was aiming for	• Analysing shots from closer to the green

					the hole or rather the area close to it	
29	James, L.P., Robertson, S., Haff, G.G., Beckman, E.M. and Kelly, V.G. (2016) 'Identifying the performance characteristics of a winning outcome in elite mixed martial arts competition', *Journal of Science and Medicine in Sport*, doi: 10.1016/j.jsams.2016.08.001	<u>*Matches*</u>: 234 <u>*Competition*</u>: 2014 Ultimate Fighter Championshi p <u>*Sport*</u>: Mixed Martial Arts	<u>*Reliability*</u>: none reported <u>*Statistics*</u>: Descriptive statistics Cohens d (effect size) Chi-square automatic interaction detector Discriminant function analyses	• The accuracy of a manoeuvre, rather than the volume executed, that is of greatest importance in determining a winning outcome. • Grappling and accuracy PIs were the most influential in explaining outcome • Decision tree models also revealed multiple combinations of PIs that lead to victory	•	•
30	Jones, P., James, N. & Mellalieu, S. (2004) 'Possession as a performance indicator in soccer', *International Journal of Performance Analysis in Sport*, 4(1), pp. 98-102.	<u>*Matches*</u>: 24 <u>*Competition*</u>: 2001-2002 English Premier League <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: % Error <u>*Intra*</u>: 0% <u>*Statistics*</u>: Mann Whitney U	• Successful teams had significantly longer possessions irrespective of match status • Both successful and unsuccessful teams had longer durations possessions when they were losing compared to when winning • Whilst matches were being own successful teams kept possession longer	• Excluded all possessions less than 3 seconds	• Further investigations into possession and how goals are scored and created – and also strategy to prevent opposition from scoring
31	Kajmovic, H., Kapur, A., Radjo, I. & Mekic, A. (2014) 'Differences in Performance between	<u>*Matches*</u>: 946 techniques <u>*Competition*</u>: 2010	<u>*Reliability*</u>: % Error <u>*Intra*</u>: <4.25% <u>*Inter*</u>: <4.08%	• Wrestler who won their matches, dominated by the techniques made in the parterre and standing position	• Did not investigate effects of penalties	• Investigate the effects of penalties in wrestling

	Winners and Defeated Wrestlers in the European Championships for Cadets', *International Journal of Performance Analysis in Sport*, 14(1), pp. 252-261.	European Championship *Sport*: Wrestling	*Statistics*: Wilcoxon Signed Rank Test			
32	Koo, D.H., Panday, S.B., Xu, D.Y., Lee, C.Y. & Kim, H.Y. (2016) 'Logistic Regression of Wins and Losses in Asia League Ice Hockey in the 2014-2015 Season', *International Journal of Performance Analysis of Sport,* 16(3), pp.871-880.	*Matches*: 432 *Competition*: Asia League Ice Hockey *Sport*: Ice Hockey	*Reliability*: none reported *Statistics*: Paired T-test Logistic regression Cohens d (effect size)	• An increase in restraining fouls sig. affects winning probability in 3rd period • Increase in restraining fouls, leads to an increase in number of chances for attempting shots in the 3rd period. • To increase chances of winning, more shots should be attempted.	• n/a	Increase accuracy of the analysis and action variables
33	Lago, C. (2009) 'The influence of match location, quality of opposition, and match status on possession strategies in professional association football', *Journal of Sports Sciences*, 27(13), pp. 1463-1469.	*Matches*: 27 Espanyol Futbal Club *Competition*: 2005-2006 Spanish Football League *Sport*: Soccer	*Reliability*: % error *Intra & Inter*: <5% *Statistics*: Linear Regression	• Possession of the ball was greater when losing than when winning or drawing • Playing against strong opposition was associated with a decrease in time spent in possession • No influence of quality of opposition on team possession	• Only analysed 1 team	• n/a
34	Lago, C. & Martín, R. (2007) 'Determinants of possession of the ball in soccer', *Journal of Sports Sciences*, 25(9), pp. 969-974.	*Matches*: 170 *Competition*: 2003-2004 Spanish League *Sport*: Soccer	*Reliability*: n/a *Statistics*: Linear regression	• Teams possession depends on evolving match status • Teams have greater possession of the ball when losing as opposed to winning or drawing • Playing at home increases possession by 6%	• Did not look at team and opposition quality	• Use the performance indicators identified to develop a model that predicts possession in

						soccer
35	Lago-Ballesteros, J. & Lago-Peñas, C. (2010) 'Performance in team sports: Identifying the keys to success in soccer', *Journal of Human Kinetics*, 25(1), pp. 85-91.	Matches: 380 Competition: 2008-2009 Spanish League Sport: Soccer	Reliability: Kappa Inter:0.95-0.98 Statistics: 1-way ANOVA Post hoc - Bonferroni	• Top teams had a higher average of goals for, total shots and shots on goal than middle and bottom teams. • Bottom teams needed a higher number of shots for scoring a goal than the other groups of teams. • Middle teams showed a lower value in assists and ball possession than top teams.	• n/a	• Analyse the relationship between performance indicators related to defence and team results
36	Lago-Peñas, C. & Dellal, A. (2010) 'Ball possession strategies in elite soccer according to the evolution of the match-score: The influence of situational variables', *Journal of Human Kinetics*, 25(1), pp. 93-100.	Matches: 380 Competition: 2008-2009 Spanish League Sport: Soccer	Reliability: Kappa Intra & Inter: 0.93-0.98 Statistics: Pearson coefficients of variation Multiple regression	• Best teams kept a higher percentage of ball possession and their patterns of play were more sTable. • Linear regression revealed that independent variables have an effect on possession strategies.	• n/a	• n/a
37	Lago-Peñas, C., Lago-Ballesteros, J. & Rey, E. (2011) 'Differences in performance indicators between winning and losing teams in the UEFA Champions League', *Journal of Human Kinetics*, 27(1), pp. 135-146.	Matches: 288 Competition: 2007-2008, 2008-2009 & 2009-2010 UEFA Champions League Sport: Soccer	Reliability: Kappa Inter: 0.92-0.95 Statistics: 1 way ANOVA Discriminant analysis	• Winning teams had outperformed opponents on total shots, shots on goal, effectiveness, passes, successful passes and ball possession. • The variables that discriminate between winning drawing and losing teams were shots on goal, crosses, ball possession, venue and quality of opposition.	• Passes and successful passes were not considered.	• Analyse the relationship between performance indicators related to defence and team results

38	Lago-Peñas, C., Lago-Ballesteros, J., Dellal, A. & Gómez, M. (2010) 'Game-related statistics that discriminated winning, drawing and losing teams from the Spanish soccer league', *Journal of Sports Science and Medicine*, 9(2), pp.288-293.	Matches: 380 Competition: 2008-2009 Spanish League Sport: Soccer	Reliability: Kappa Intra & Inter: 0.95-0.98 Statistics: Univariate T-Test Discriminant analysis	• Winning outperformed opponents on total, shots on goal, effectiveness, assists, offsides committed and crosses against. • The variables that discriminate between winning drawing and losing teams were total shots, shots on goal, crosses, crosses against, ball possession, and venue.	• n/a	• Analyse the relationship between performance indicators related to defence and team results
39	Lames, M. & McGarry, T. (2007) 'On the search for reliable performance indicators in game sports', *International Journal of Performance Analysis in Sport*, 7(1), pp. 62-79.	Qualitative	N/a	• Performance indicators are inherently unsTable as most sports are viewed as a dynamic interaction process between two opponents. • Alternative approaches need to be investigated – that include dynamical considerations	• n/a	• Mathematical modelling and simulation techniques should be used and include qualitative methods
40	Liu, H., Gomez, M., Lago-Peñas, C. & Sampaio, J. (2015) 'Match statistics related to winning in the group stage of 2014 Brazil FIFA World Cup', *Journal of Sports Sciences*, 33(12), pp.1205-1213.	Matches: 64 Competition: 2014 World Cup Sport: Soccer	Reliability: n/a Statistics: K-means cluster analysis Generalised linear Modelling	• Shot, Shot on Target, Shot from Counter Attack, Shot from Inside Area, Ball Possession, Short Pass, Average Pass Streak, Aerial Advantage and Tackle all had positive effects on probability of winning	• Only analysed within-team effect	• Analyse the between team effect from differences between team values
41	Meletakos, P., Vagenas, G. & Bayios, I. (2011) 'A multivariate assessment of offensive performance indicators in Men's Handball: Trends and differences in the World	Matches: 288 Competition: 2005, 2007 & 2009 Mens World Handball	Reliability: Kappa Inter: 0.991 Statistics: Kolmogorov-Smirnov tests	• 9 meter efficacy remained relatively constant throughout the three competition years • Multivariate difference among the three championships on all six performance indicators were evident	• n/a	• Analyse the effect of anthropometric and physical fitness, quality of opponents, referee bias and

	Championships', *International Journal of Performance Analysis in Sport*, 11(2), pp. 284-294	Championship *Sport*: Handball	MANOVA Univatiate F tests	• Players had good adaptive defensive tactics		other independent variables
42	Mikołajec, K., Maszczyk, A. & Zając, T. (2013) 'Game Indicators Determining Sports Performance in the NBA', *Journal of Human Kinetics*, 37(1), pp. 145-151.	*Matches*: All from below competition dates *Competition*: 2003-2011 NBA Leagues *Sport*: Basketball	*Reliability*: N/A *Statistics*: Factor analysis Cluster analysis Model econometrics	• Performance indicators were identified, as Win%, Offensive EFF, 3rd Quarter PPG, Win% CG, Avg Fauls and Avg Steals • An increase in any parameter leads to improved ranking	• n/a	• n/a
43	Milanović, D., Sporiš, G. & Vuleta, D. (2015) 'Indicators of situational efficiency of winning and defeated male handball teams in matches of the Olympic tournament 2012', *Acta Kinesiologica*, 9(1), pp. 40-49.	*Matches*: 30 *Competition*: 2012 Olympic Handball games *Sport*: Handball	*Reliability*: n/a *Statistics*: Mann-whitney U	• Significant differences were evident between winning and defeated teams in variables: shoot from 9 meters-successfully, shoot from the wing position-successfully, shoot from the wing position-unsuccessfully, shoot from 6 meters-unsuccessfully, shoot from 7 meters-successfully, assistance, lost balls-turnovers and blocked balls	• n/a	Trends of changes in certain variables • Situational performance of handball teams in various competitions
44	Najdan, M., Robins, M. & Glazier, P. (2014) 'Determinants of success in English domestic Twenty20 cricket', *International Journal of Performance Analysis in Sport*, 14(1), pp. 276-295.	*Matches*: 59 innings *Competition*: 2010 English Domestic Twenty20 *Sport*: Twenty20 Cricket	*Reliability*: Kappa *Intra*: 0.96, 0.84, 0.71 *Inter*: 0.91, 0.81, 0.65 *Statistics*: Medians Means	• Top 5 indicators were losing less wickets in the powerplay overs, losing less wickets between overs 7-10, 50+ run partnerships, individual batsmen contributing 75+ runs and 50-74 runs • Winning teams scored a higher percentage of total runs to long-off and the off-side, and bowled a higher percentage of deliveries at a yorker and short length than losing team	• subjectivity of the delivery length results (Use Hawk-Eye technology instead) • Did not differentiate	• Different styles of bowlers should be analysed • Investigate performance according to opposition quality

			Effect sizes		between the different styles of bowlers	
45	O'Donoghue, P. (2008) 'Principal components analysis in the selection of key performance indicators in sport', *International Journal of Performance Analysis in Sport*, 8(3), pp. 145-155.	*Matches*: 146 *Competition*: 2007 Australian and US Open *Sport*: Tennis	*Reliability*: % error *Inter*: <5% one over 10% *Statistics*: Chi square Varimax rotation procedure	• 13 of 24 performance indicators were significantly different between winning and losing performances • There were 4 key performance indicators that significantly distinguished between winning and losing players % First serve points played to left, % points where the player played a winner, mean speed of counting serves, % points where the player played unforced error • Combine logically related PIs to create KPI	• A disadvantage of principal components analysis is that all of the variables entered are considered to be equally important	• n/a
46	Ohnjec, K., Vuleta, D., Milanović, D. & Gruić, I. (2008) 'Performance indicators of teams at the 2003 world handball championship for women in Croatia', *Kineziologija*, 40(1), pp. 69-79.	*Matches*: 60 *Competition*: Womens World Championship *Sport*: Handball	*Reliability*: n/a *Statistics*: Simple regression MANOVA	• Winning teams took on average 3.55 shots more that the defeated teams • From the backcourt positions the winning teams took 19.76 shots on average • Winners were more frequently in the position to perform a fast break	• Only fragments of the complexity of the game of handball were covered	• Develop the way of recording and assessing performance to facilitate a comparison of performance of national handball competitions
47	Ordóñez, E., Gonzalez, C. & Pérez, M. (2015) 'Offensive Performance Indicators in a Regular Season of Water-Polo', *International Journal*	*Matches*: 88 *Competition*: 2011-2014 Spanish Pro	*Reliability*: Kappa = 0.97 *Statistics*:	• Winning games had averages that were significantly higher for counterattack, shots, goals and shots from zones close to the goal.	• n/a	• n/a

	of Performance Analysis in Sport, 15(3), pp. 1114-1123.	Water-Polo league Sport: Water polo	One-way ANOVA Kruskal-Wallis Discriminant analysis	• Losing games had significantly higher averages in even attacks, shots, no goal shots and shots that originated from zones 2 (further away).		
48	Ortega, E., Villarejo, D. & Palao, J. (2009) 'Differences in game statistics between winning and losing rugby teams in the Six Nations Tournament', *Journal of Sports Science and Medicine*, 8, pp. 523-527	Matches: 58 Competition: 2003, 2004, 2005 & 2006 6 Nations Sport: Rugby Union	Reliability: n/a Statistics: Mann-Whitney U Discriminant analysis	• winning teams had averages that were significantly higher for the following variables: points scored, tries, conversions and successful drops for the group points scored • the two variables that discriminated between winners and losers were tries and conversions	• n/a	n/a
49	Palao, J. & Ortega, E. (2015) 'Skill efficacy in men's beach volleyball', *International Journal of Performance Analysis in Sport*, 15(1), pp. 125-134.	Matches: 84 Competition: 2008 Wortld Tour Beach Volleyball Sport: Beach Volleyball	Reliability: Kappa Intra: 0.98 Inter: 0.87 Statistics: Student t test Discriminant analysis	• Winning teams had higher coefficients and efficacy for serve, reception, set and side-out spike. • Winning teams differentiated from losing teams by the serves that allowed no attack options, block points, serve points and counter-attack points	• n/a	• Further studies are needed to understand beach volleyball game patterns
50	Pratas, J., Volossovitch, A. & Carita, A. (2016) 'The effect of performance indicators on the time the first goal is scored in football matches', *International Journal of Performance Analysis in Sport*, 16(1), pp. 347-354.	Matches: 240 Competition: 2009/10 Portuguese Premier League Sport: Soccer	Reliability: n/a Statistics: Survival analysis Cox regression Descriptive analysis Student t-test	• A greater goal difference and a larger number of shots on goal had a positive significant influence on the time the first goal was scored in the match by the home teams • Disciplinary sanctions and substitutions had a negative significant effect on the time of the first goal	• n/a	Investigate how coaches can use substitutions to increase probability of scoring the first goal Investigate how PIs influence the

						time of scoring
51	Prim, S., van Rooyen, M. & Lambert, M. (2006) 'A comparison of performance indicators between the four South African teams and the winners of the 2005 Super 12 Rugby competition. What separates top from bottom?', *International Journal of Performance Analysis in Sport*, 6(2), pp. 126-133.	Matches: 9 Competition: 2005 Super 12 Competition Sport: Rugby Union	Reliability: % error Intra: <5% Statistics: ANOVA Kruskall-Wallis	• No differences for total amount of ball possession per match or duration of each movement involving ball possession • No significant differences between the number of unsuccessful tackles made, possession per number of offloads made, opposition possession per number of offloads by opposition, opposition possession per tackle.	• Low sample size	Investigate whether visually striking box and whisker plot is a valid form of data analysis
52	Puente, C., Coso, J. & Salinero, J. (2015) 'Basketball performance indicators during the ACB regular season from 2003 to 2013', *International Journal of Performance Analysis in Sport*, 15(3), pp. 935-948.	Matches: 3060 Competition: 2003-2013 Spanish Pro Basketball League Sport: Basketball	Reliability: n/a Statistics: Confidence intervals Pearson correlation Multiple regression 1-way ANOVA Effect sizes	• Teams grouped according to final ranking • Accuracy in 2-point field goals and the total number of assists were best correlated with the number of wins. • Shooting accuracy and number of rebounds explained the variance for the number of wins in a season	• n/a	• n/a
53	Quarrie, K. & Hopkins, W. (2014) 'Evaluation of goal kicking performance in international rugby union matches', *Journal of Science*	Matches: 582 Competition: 2002-2011 Various International	Reliability: n/a Statistics: Generalised Linear Mixed Model	• 72% of the 6769 kick attempts were successful • 45% of points scored during matches were from goal kicks • 5.7% of matches hinged on the outcome of a kick attempt	• n/a	• The modelling approach in this study could be applied to other performance indicators in rugby

	and Medicine in Sport, 18(2), pp. 195-198.	Rugby Matches <u>*Sport*</u>: Rugby union		• Large decrease in success of kicks as distance increased		and in other sports
54	Robertson, S., Back, N. & Bartlett, J. (2016) 'Explaining match outcome in elite Australian Rules football using team performance indicators', *Journal of Sports Sciences*, 34(7), pp. 637-644.	<u>*Matches*</u>: 396 <u>*Competition*</u>: 2013 & 2014 AFL League <u>*Sport*</u>: Australian Rules Football	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Descriptive statistics ANOVA Logistic Regression Chi Squared Automatic Interaction Detection	• Analysis revealed relative differences for kicks and goal conversion which both explained match outcome • Two models achieved 88.3% and 89.8% classification accuracies • Models incorporating less PIs explained match outcome to a lesser extent (81.0% and 81.5% for logistic regression and CHAID, respectively). However, both were fit to • The CHAID model revealed multiple winning performance indicator profiles	Low sample size and did not use independent variables to differentiate team and opponent quality	Expanded to use physiological indicators Analyse game by duration Compare win/loss with margin as margin may give better insight
55	Robertson, S., Gupta, R., & McIntosh, S. (2016) 'A method to assess the influence of individual player performance distribution on match outcome in team sports', *Journal of Sports Sciences*, 34(19), pp. 1893-1900.	<u>*Matches*</u>: 198 <u>*Competition*</u>: 2014 AFL League <u>*Sport*</u>: Australian Rules Football	<u>*Reliability*</u>: Intra-class Correlation Coefficients Inter = 0.947-1.000 <u>*Statistics*</u>: Generalised Linear Model (GEE) ANOVA	• Player values were converted to a percentage of team total for 11 PIs • Generalised estimating equation model explained match outcome at a median accuracy of 63.9% • Lower 75th, 90th & 95th percentile values fore team goals and higher 25th and 50th percentile values for disposals were linked with winning.	Lack of inter and intra reliability Lack of validity data for each PI	Investigate external validity of model – on future seasons Analyse differences within and between positional groups
56	Ross, A., Gill, N., Cronin, J. & Malcata, R. (2016) 'Defensive and attacking performance indicators in	<u>*Matches*</u>: 87 <u>*Competition*</u>: 2013 IRB Sevens World	<u>*Reliability*</u>: Intra-class Correlation Coefficients Intra: > 0.87	• All attacking and defensive indicators had clear within and between team effects on points scored and conceded	Limited to a single tournament when	Investigate the effect of physical characteristics on individual match

	rugby sevens', *International Journal of Performance Analysis in Sport*, 16(2), pp. 569-580.	Series & 2013-14 IRB Sevens World Series *Sport*: Rugby 7s	Inter: > 0.80 *Statistics*: Descriptive statistics General linear mixed effects models	• Line breaks had strongest relationship with points scored • Teams should increase dominance in tackles	analysing multiple teams and single team when analysing multiple tournaments	performance
57	Ruiz-Ruiz, C., Fradua, L., Fernandez-GarcIa, A. & Zubillaga, A. (2013) 'Analysis of entries into the penalty area as a performance indicator in soccer', *European Journal of Sport Science*, 13(3), pp. 241-248.	*Matches*: 64 *Competition*: 2006 World Cup *Sport*: Soccer	*Reliability*: Kappa *Intra*: 0.93-0.98 *Inter*: 0.88-0.98 *Statistics*: 1 way ANOVA Chi square Phi coefficient Cramers V	• winning teams received significantly fewer entries into their own penalty area • Teams that received more entries into their own penalty area than the opposing team were significantly more likely to concede a goal • Player dismissal is disadvantageous for entries to penalty area	Analysing the interaction among other variables will lead to a better understanding	Examining the quality of offensive performance Indicators Investigate effects of independent variables on penalty area entries
58	Sánchez-Moreno, J., Marcelino, R., Mesquita, I. & Ureña, A. (2015) 'Analysis of the rally length as a critical incident of the game in elite male volleyball', *International Journal of Performance Analysis in Sport*, 15(2), pp. 620-631.	*Matches*: 36 *Competition*: 2010 Mens World Championship & 2011 FIVB Mens World League *Sport*: Volleyball	*Reliability*: Kappa *Intra*: .82-.92 *Inter*: .84-.91 *Statistics*: Logistic regression	• Winning a long rally increased 1.65 times the probability of winning the following rally compared to short rallies and 1.62 times in comparison with medium rallies • Receiving teams won 73.7% of short rallies • The smaller the duration of rally length the smaller chance of losing the point, whereas the longer duration their higher probability of losing the point.	n/a	n/a
59	Scholes, R. & Shafizadeh, M. (2014) 'Prediction of successful performance from fielding indicators in cricket:	*Matches*: 17 *Competition*: 2012 Twenty20	*Reliability*: N/A *Statistics*:	• Fielding indicators were significant predictors of match outcome	No reliability conducted on data	Future research in the area of fielding is needed

	Champions League T20 tournament', *Sports Technology*, 7(1-2), pp. 62-68.	Sport: Twenty20 Cricket	Discriminant analysis Canonical correlations	• Catches inside the 30yd circle and outside the 30yd circle were significant predictors of match outcome	Sample size	
60	Shafizadeh, M., Taylor, M. & Peñas, C. L. (2013) 'Performance Consistency of International Soccer Teams in Euro 2012: a Time Series Analysis', *Journal of Human Kinetics*, 38, pp. 169-177.	Matches: 38 Competition: 2012 Euro Soccer Sport: Soccer	Reliability: n/a Statistics: Autocorrelation Cross-correlation	• Goal related and offensive-related indicators played a significant role in successful performance in international tournament soccer • Performance consistency is more significant in international tournament soccer	n/a	n/a
61	Taylor, J., Mellalieu, S., James, N. & Barter, P. (2010) 'Situation variable effects and tactical performance in professional association football', *International Journal of Performance Analysis in Sport*, 10(3), pp. 255-269.	Matches: 47 Competition: Professional Association Football Sport: Soccer	Reliability: % error Intra: Passes: <2%, area of pitch:<5% Inter: Passes:<2%, area of pitch:<5% Statistics: Log Linear Modelling	• Distribution of passes across pitch were influenced by independent variables • occurrence of passes performed by the team varied as an interactive function of independent variables • Technical and tactical components of soccer are affected by independent variables	Analysed 1 team Sample size – is it sufficient for the log linear modelling?	Examine alternative methods for assessing the impact of situation variables upon football performance
62	Vahed, Y., Kraak, W., & Venter, R. (2014). The effect of the law changes on time variables of the South African Currie Cup Tournament during 2007 and 2013. International Journal of Performance	Matches: 70 Competition: 2007 & 2013 South African Currie Cup Tournament Sport: Rugby Union	Reliability: % agreement Intra: >95% Statistics: Mixed model ANOVA	• Time interval profiles revealed total match time and total stoppage time increased significantly • Total ball in play time decreased significantly • Total tackle time increased significantly	n/a	Compare differences between competitions Investigate effects of changes in English, European

	Analysis in Sport, 14(3), 866-883.					domestic competitions.
63	Vaz, L., Mouchet, A., Carreras, D. & Morente, H. (2011) 'The importance of rugby game-related statistics to discriminate winners and losers at the elite level competitions in close and balanced games', *International Journal of Performance Analysis in Sport*, 11(1), pp. 130-14.	*Matches*: 284 *Competition*: 2003-2006 IRB Competitions & Super Rugby *Sport*: Rugby Union	*Reliability*: Kappa *Inter*: >0.91 *Statistics*: ANOVA Discriminant analysis	• Differences evident between competitions • Differences evident between groups of closed and balanced games • International competitions s are unlikely to show differences between winning and losing teams • Missed tackles and line outs most influential variables	n/a	n/a
64	Vaz, L., Van Rooyen, M., & Sampaio, J. (2010) 'Rugby game-related statistics that discriminate between winning and losing teams in IRB and Super twelve close games', *Journal of sports science & medicine*, 9(1), pp.51.	*Matches*: 224 *Competition*: 2003-2006 IRB Competitions & Super Rugby *Sport*: Rugby Union	*Reliability*: Kappa *Inter*: >0.91 *Statistics*: ANOVA Discriminant analysis	• The discriminant functions were statistically significant for Super Twelve games but not for IRB games • Winners and losers were discriminated by possessions kicked, tackles made, rucks and pass, passes completed, mauls won, turnovers won, kicks to touch and errors made in IRB games.	n/a	Investigate if the location on the field where the lineout was lost might be of more significance than just the frequency of how many lineouts were lost
65	Vila, M., Abraldes, J., Alcaraz, P., Rodriguez, N. & Ferragut, C. (2011) 'Tactical and shooting variables that determine win or loss in top-Level in water polo', *International Journal of*	*Matches*: 72 *Competition*: 2008 Euro Championship and 2009 World	*Reliability*: Kappa *Intra*: >92% *Inter*: >87% *Statistics*: Kruskal-Wallis	• Winning teams in Euro Championship performed the following measures differently to losing teams; definition, resolution of shots, resolution of shots at goal, efficacy of detention of shots at goal and inaccuracy of shots at goal.	Did not investigate the possibility of behavioural changes that could appear	n/a

	Performance Analysis in Sport, 11(3), pp. 486-498.	Championship *Sport*: Water Polo	ANOVA	• Accuracy of shots have most influence on differences between winning and losing teams	as a function of the difference in goal score in the final result and the effect of the competition.	
66	Villarejo, D., Palao, J., Ortega, E., Gomez-Ruano, M. & Kraak, W. (2015) 'Match-related statistics discriminating between playing positions during the men's 2011 Rugby World Cup', *International Journal of Performance Analysis in Sport*, 15(1), pp. 97-111.	*Matches*: 48 *Competition*: 2011 Rugby World Cup *Sport*: Rugby Union	*Reliability*: Intra-class Correlation Coefficient *Inter*: >.960 *Statistics*: Univariate tests Discriminant analysis	• Front rows from winning teams scored more tries and won more turnovers • Second rows from winning teams performed better in line breaks, try assists, tries and offloads • Kicking game of scrumhalf is important in regards to match outcome • Winning players had greater participation	Did not analyse independent variables	Develop player profiles Include effects of independent variables
67	Vinson, D. and Peters, D.M. (2016) 'Position-specific performance indicators that discriminate between successful and unsuccessful teams in elite women's indoor field hockey: implications for coaching', *Journal of sports sciences*, 34(4), pp. 311-320.	*Matches*: 36 *Competition*: 2011-12 England Hockey Women's Premier League *Sport*: Field Hockey	*Reliability*: Kappa *Intra: k > 0.90* *Inter*: *k > 0.85* *Statistics*: Percentiles MANOVA Kruskal-Wallis H Discriminant analysis	• Successful passing in related teams was significantly lower than in mid Table and qualifying teams in four of the five outfield positions • The right backs of qualifying teams demonstrated significantly fewer unsuccessful passes and interceptions than relegated teams. • The right forwards of relegated teams demonstrated sig fewer successful interceptions than qualifying teams and sig more unsuccessful interceptions than mid-Table teams.	It was difficult to determine whether players had changed positions/roles during the game Length of time not monitored for relative	Investigate pressing strategies Investigate proximity of the forwards to the ball carrier when play commences

					contributions Sample only one competition	
68	Vogelbein, M., Nopp, S. & Hökelmann, A. (2014) ‘Defensive transition in soccer–are prompt possession regains a measure of success? A quantitative analysis of German Fußball-Bundesliga 2010/2011’, *Journal of Sports Sciences*, 32(11), pp. 1076-1083.	<u>*Matches*</u>: 306 <u>*Competition*</u>: 2010/2011 German Bundesliga Season <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: <u>*Intra*</u>: 0.910 (Cronbachs) <u>*Inter*</u>: 0.898 (Kappa) <u>*Statistics*</u>: Kruskal-Wallis Mann-Whitney U Friedmans Wilcoxon Bonferroni Cohens D	• Top teams recovered ball possession quickest after losing it and had lower defensive reaction times ~1sec • All groups showed lowest defensive reaction times when trailing • Recovering ball possession quickly is important in determining successful defensive performance	Did not look at opponent interaction	Find more qualitative measures to identify the underlying mechanisms of prompt ball possession recoveries and include international competitions in the analyses.
69	Winter, C. & Pfeiffer, M. (2016) ‘Tactical metrics that discriminate winning, drawing and losing teams in UEFA Euro 2012®', *Journal of Sports Sciences*, 34(6), pp. 486-492.	<u>*Matches*</u>: 27 <u>*Competition*</u>: UEFA Euro 2012 <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: Cohens Kappa Inter: 0.89 (Kappa) <u>*Statistics*</u>: Descriptive statistics Factor analysis Discriminant analysis	• 11 tactical metrics (defined by Optikick) model tactical behaviour in 4 different dimensions (game speed, transition play after ball recovery, transition play after ball loss and offence efficiency (OE)). • Discriminant analysis based on the factor values enabled 64.8% correct identification of winners, losers and drawers. • Transition play after losing the ball and the attack efficiency seem to be directly related to match outcome	n/a	Take the location on the pitch into account.
70	Woods, C. (2016) ‘The use of team performance	<u>*Matches*</u>: 394	<u>*Reliability:* non reported</u>	• Hit-outs, clearances & inside 50m were significantly related to ladder position	Playing draw not equal,	Investigate physical profiles of

	indicator characteristics to explain ladder position at the conclusion of the Australian football league home and away season', *International Journal of Performance Analysis in Sport*, 16(3), pp. 837-847.	*Competition*: 2015 AFL League *Sport*: Australian Rules Football	*Statistics:* Cumulative linked mixed models	• All decreased as ladder position increased (team quality decreased)	some teams could play each other more than once.	AFL teams according to team quality Improve and expand the PIs used in the study
71	Woods, C., Bruce, L., Veale, P. & Robertson, S. (2016) 'The relationship between game-based performance indicators and developmental level in junior Australian football: Implications for coaching', *Journal of Sports Sciences*, 34(23), pp. 2165-2169	*Matches*: 28 *Competition*: 2014 U16 & U18 National Championships *Sport*: Australian Rules Football	*Reliability*: none reported *Statistics*: Descriptive statistics Effect size (Cohens d) Generalised linear modelling	• Contested marks and contested possessions discriminate gameplay at u18 levels • Total marks and clearances discriminate gameplay at u16 levels • Coaches at u16 level should promote simplistic open game styles. Ensuring players develop clearing actions and marking skills in game based situations.	n/a	Explore technical differences between elite junior and senior developmental levels PIs Explore differences at position-specific level
72	Woods, C., Sinclair, W. and Robertson, S. (2017) Explaining match outcome and ladder position in the National Rugby League using team performance indicators. To be published in *Journal of Science and Medicine in Sport* [preprint]. Available at: http://dx.doi.org/10.1016/j.jsams.2017.04.005 (Accessed: 15 May 2017)	*Matches*: 188 *Competition*: 2016 NRL League *Sport*: Rugby league	*Reliability*: none reported *Statistics*: Ordinal regression CI classification tree Cohens D	• 5 PIs were retained by the CI trees; try assists, all run metres, line breaks, dummy half runs and offloads. • 3 PIs had significant relationship with ladder position, missed tackles, kick metres and dummy half runs	Playing draw not equal No reliability	Consider combining multiple actions, investigate the chain of play that led to a specific action. Include independent variables

2.4. PERFORMANCE PROFILING PAPERS

2.4.1 INTRODUCTION

Performance profiles are a collection of action variables and performance indicators that are used to represent typical performances of individual athletes and or teams (Hughes, Evans and Wells, 2001; Liu, Yi, Gimenez, Gomez & Lago-Penas, 2015; O'Donoghue, 2013). The two main methodologies of performance profiling in performance analysis have used confidence intervals of medians (James et al., 2005) and quantiles (O'Donoghue, 2005). However, a more recent alternative technique has been archetypal analysis (Eugster, 2012) although this has not been widely adopted, with newer research by Liu et al. (2015) revisiting O'Donoghue's (2005) technique addressing the recommendations for future research by including independent variables such as opponent strength in their profiling methodology to give more context and produce informative and meaningful profiles. Similarly, Vinson and Peters (2016) and Liu, Gomez, Goncalves and Sampaio (2016) expanded upon previous methods (James et al., 2005; O'Donoghue, 2005) with Liu et al. (2016) also including the effect sizes and using opposition quality, match outcome and match location to provide more context to the results. One of the key themes in performance profiling is to understand what size the sample has to be in order for profiles to be a true and accurate reflection of performance (Hughes et al., 2001; James et al., 2005). James et al. (2005) suggested that performance profiles may never stabilise due to unpredictability of individual players. However, this area remains relatively under-researched with Hughes et al. (2001) developing a simple methodology to establish how many matches were needed for the average of a performance indicator to stabilise. Firstly, the mean value of the action variables was calculated with matches being analysed in chronological order to understand how the evolving mean changes as more matches are added. Secondly, tolerable percentages of the typical mean can be set as the evolving mean stabilises, although this may vary between different indicators. Hughes et al. (2001) give examples of passing in hockey which may stabilise after 5 matches, or crosses which may stabilise after 10 matches and finally shots which may take 30 matches to stabilise. Once the number of matches required for each indicator is established then the researcher can collect data accordingly and the profile should be representative of performance. However, O'Donoghue (2005) criticises this method as the technique risks a meaningful difference being shown as being tolerable and that the word normative has been used by Hughes et al. (2001) despite the methods not indicating any normative methodology. Another criticism of some of the profiling papers is that they try to compare different positions/positional groups on team performance indicators. For example, there are eighteen different positions in Australian rules football, ten in rugby union, nine for rugby league and four in Hockey. Therefore, these approaches of using team PIs to explain positional differences may not be always appropriate and perhaps identifying PIs for each positional group will yield more informative results. Furthermore, there could be some common PIs identified across all groups and therefore these could be considered to compare between groups.

2.4.2. JAMES ET AL. (2005) METHODS

A profiling study carried out by James et al. (2005) analysed twenty-two domestic matches of a professional rugby union team. Action variables were listed by the three authors who had a combined experience of 50 years in rugby union and 40 years in performance analysis, relative to the various positions each team has within rugby union, however only action variables that the authors qualitatively thought, according to their expertise, were indicative of successful and unsuccessful performance were included for each position and indicators that were common across positions. This list was then subjected to coach validation by three elite level rugby union coaches, with a combined playing and coaching experience of fifty years, who altered the list accordingly. However, Butterworth et al. (2013) suggest that a wider pool of coaches may have yielded more objective results. A similar process was followed for developing the operational definitions for the subsequent analysis of the matches. Rugby union matches last 80 minutes (exclusive of stoppage time), however players do not always play whole matches due to injury or substitutions therefore the authors decided to transform the data to account for the time an individual player was on the field. Due to the data being non-parametric the authors used medians and confidence limits, with 95% confidence limits calculated for each performance indicator as data was added. The use of confidence intervals allows for the comparisons of performances which is useful for coaching staff and could potentially be used when trying to complete a team list pre and post-match. However, this method has drawn some criticism with Butterworth et al. (2013) who commented that although this method does give an accurate reflection of typical performance it does not take into account the full range of values at that level, however, this was a questionable comment as the median is an appropriate measure of central tendency for non-parametric data. James et al. (2005) then calculated median values and confidence limits for the performance indicators enabling performance profiles to be created for each player position within the team (n=10). This allowed for inter (Figure 2.1) and intra-positional analysis to take place, with general positional profiles being successfully constructed, and further to this differences between players within the particular position were identified which the authors attributed down to individual differences in styles of play. Butterworth et al. (2013) provided some criticisms commenting that this method leaves out lesser occurring actions that may still be critical to performance, however this could be improved by identifying performance indicators and key performance indicators as defined earlier in this chapter to justify reduced variables for profiles. However, the use of bar and line charts are an effective method for presenting results in rugby union although the transferability of this particular method to other sports could require some modification.

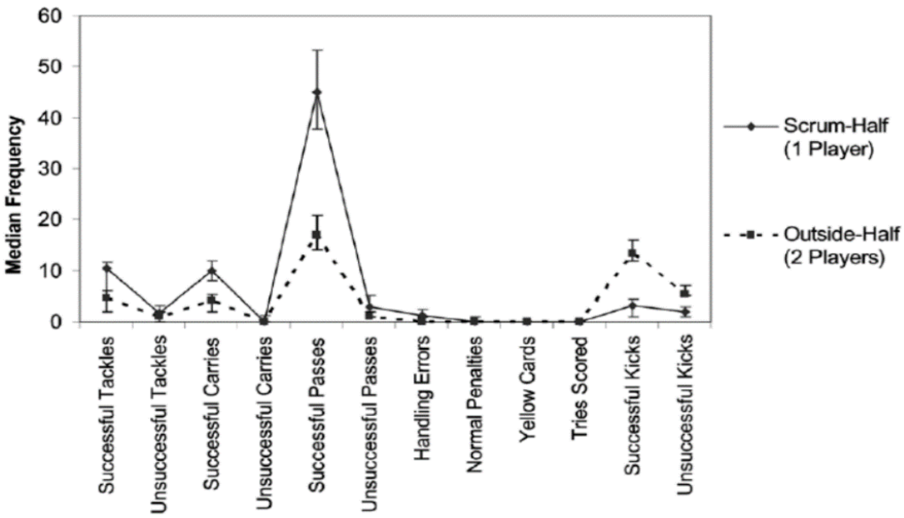


Figure 2.1. Line chart use to show variation between positions (James et al., 2005).

2.4.3 VINSON AND PETERS (2016) METHODS

Vinson and Peters (2016) developed positional PIs in Women's Indoor Hockey that discriminated between top, middle and bottom quality teams. Following similar methods to James, Mellalieu and Jones (2005) they first identified action variables in consultation with experienced hockey coaches. Positional profiles were calculated using medians and confidence limits (95%), data was then transformed to z scores. Positional differences were analysed using MANOVA tests and finally discriminant analysis was used to determine if the variables identified would predict whether a team would reach the top four or bottom two based on their performances on the identified action variables (Table 2.3).

Table 2.3. Discriminant function structure coefficients for the outfield positions across ranking groups

	Left back		Right back		Centre		Left forward		Right forward	
	Func. 1	Func. 2	Func. 1	Func. 2	Func. 1	Func. 2	Func. 1	Func. 2	Func. 1	Func. 2
Successful pass	0.75	−0.33	−0.53	0.77	0.68	0.33	0.76	−0.05	−0.68	0.51
Unsuccessful pass	−0.06	0.51	0.42	0.36	−0.50	0.38	0.32	0.51	0.08	−0.01
Successful interception	0.08	0.50	−0.04	0.24	−0.02	−0.33	−0.19	0.25	0.30	0.66
Unsuccessful interception	−0.02	0.23	0.45	0.20	−0.04	0.67	−0.38	0.17	0.62	0.06
Dribble	0.19	0.31	−0.31	0.11	0.30	−0.42	0.25	0.12	−0.42	0.26
Successful tackle	−0.31	0.15	−0.08	0.32	0.12	−0.33	0.20	−0.14	0.02	−0.01
Unsuccessful tackle	−0.18	−0.16	0.09	0.34	0.29	0.61	0.16	0.05	0.00	0.34
Foul	0.11	0.55	0.08	0.24	0.12	−0.61	−0.01	0.71	0.50	0.21
Wilks' Lambda	0.65[†]	0.95	0.33[†]	0.80	0.57[†]	0.85	0.59[†]	0.83	0.50[†]	0.75
Chi-Square	28.60[†]	3.19	72.17[†]	14.66	36.93[†]	10.54	34.50[†]	12.59	46.06[†]	18.48
P	0.027[†]	0.866	<0.001[†]	0.041	0.002[†]	0.160	0.005[†]	0.083	<0.001[†]	0.010
Eigenvalue	0.47	0.05	1.41	0.25	0.50	0.18	0.40	0.21	0.52	0.33
Relative percentage	90.5	9.5	84.9	15.1	74.0	26.0	65.2	34.8	61.6	38.4
Squared canonical correlation	0.32	0.05	0.58	0.20	0.33	0.15	0.28	0.17	0.34	0.25

Note: [†]Relates to the combination of both functions, i.e. "functions 1 through 2".

Whilst the title stated position specific performance indicators, it is clear that the authors had identified team action variables through a coach led selection process and then compared performances on those variables between the positional groups. This method builds upon James et al. (2005) by determining whether the variables identified would predict team quality.

2.4.4 O'DONOGHUE ET AL. (2005) METHODS

O'Donoghue (2005) proposed another method for creating normative performance profiles and demonstrated the methodology using tennis data. Normative performance percentiles were calculated for each performance indicator in increments of 5% up to 95%, although the author suggested that the increments could vary according to the particular database used. The mean and standard deviations were calculated for each performance indicator. The particular participant's performances were related to the normative data whilst including the lower and upper quartiles to represent the spread as this captured 50% of performances irrespective of the distribution of the particular performance indicators, finally radar charts were used to compare the performance indicators (Figure 2.2). O'Donoghue (2005) advocated the use of independent variables for future performance profiling research. Butterworth et al. (2013) criticises the method used by O'Donoghue (2005) as only being applicable for analysing a single performance. Furthermore, the use of means for non-parametric data seems strange as it is typically associated with parametric data, especially when combined with the inter-quartile range which is associated with non-parametric data.

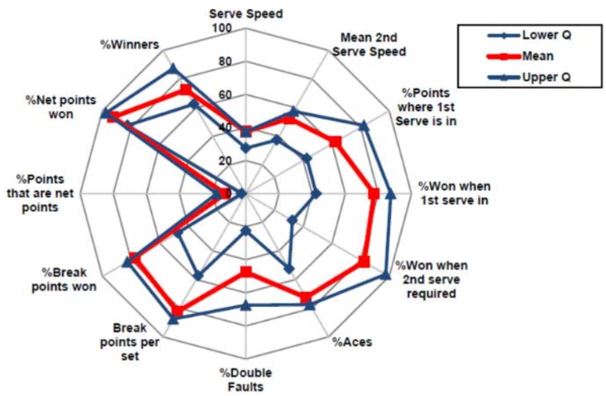


Figure 2.2. An example of a radar chart used to illustrate tennis performance

2.4.5 LIU, YI, GIMENEZ, GOMEZ AND LAGO-PENAS (2015) METHODS

Liu, Yi, Gimenez, Gomez and Lago-Penas (2015) followed the suggestions for future research from O'Donoghue (2005) and past research that had revealed soccer teams play differently when teams won, drew or lost matches (Castellano et al., 2012; Lago-Penas et al., 2010., Lago-Penas et al., 2011), when playing home or away (Gomez et al., 2012; Lago, 2009; Lago-Penas & Lago-Ballesteros, 2011; Taylor et al., 2010; Taylor et al., 2008) and finally based on their own strength and the opposition's strength (Lago, 2009; Lago-Penas et al., 2010; Taylor et al., 2008) therefore Liu et al. (2015) decided to create performance profiles for soccer teams based on three independent variables; how strong the team and opponent was rated (team and opponent team quality), whether the match was played home or away (match location) and whether the game was won or lost (match outcome). Liu et al. (2015) used four hundred and ninety-six matches from the 2009-2010 through to the 2012-2013 UEFA Champions League competitions. Action variables were then grouped into three categories based on previous literature (Castellano et al., 2012, Lago-Penas & Ballesteros., 2011; Lago-Penas et al., 2010; Lago-Penas et al., 2011; Liu et al., 2013) namely variables relating to scoring, variables related to attacking and passing and finally variables related to defending. The authors also refer to games being either balanced or unbalanced, this is where the goal difference represents whether the game was close (i.e. goal difference <3) and therefore the match represented good performances from both teams or unbalanced (i.e. goal difference ≥ 3), the cut-off values were determined by a k-means cluster analysis with 96 games being identified as unbalanced and 400 as close (balanced) games, the unbalanced matches were then removed from the analysis. Team strengths were also classified through the use of k-means cluster analysis of participating teams UEFA season club points system with twelve high level teams (points ranging from 26.67 to 36.67), 39 intermediate level teams (points ranging from 16.05 to 26.02) and finally 39 low level teams (points ranging from 4.55 to 15.23). Liu et al. (2015) developed performance profiles of overall performance and for each independent variable for teams of all three strengths using the methodology proposed by O’Donoghue (2005) by including the mean, standard deviation, median and lower and upper quartiles of frequencies from action variables. Means were also compared through the use of one-way ANOVA and independent sample-t test. In addition, all action variables were transformed into standardised scores, enabling the means, medians, lower and upper quartiles of all variables to be plotted into the same radar chart according to team strength and the three independent variables enabling for meaningful comparisons to be made in context. However the profile chart shown in Figure 2.3 shows different scales for high, intermediate and low quality ranked team's profiles, therefore making the Figure hard to understand and make fair comparisons from. Furthermore, this paper defined the team and opposition quality based on final league standing. However, as discussed earlier in this review, this method of assessing team and opposition quality/form could be developed further and various measures could be used in addition or in replacement of using previous year league ranking alone e.g. current and or cumulative form.

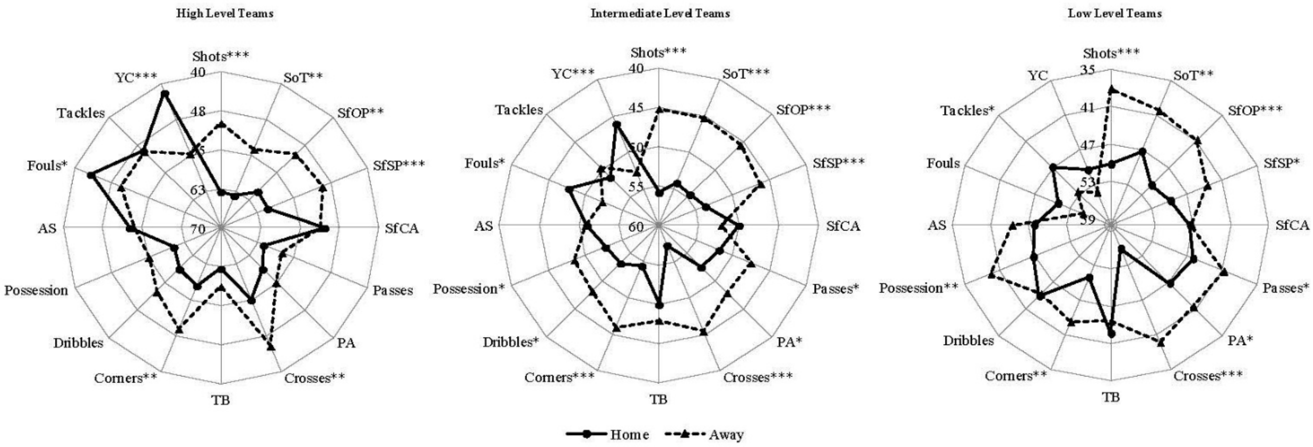


Figure 2.3. Radar charts comparing performances according to team quality (Liu et al., 2015)

2.4.6 LIU, GOMEZ, GONCALVES AND SAMPAIO (2016) METHODS

Liu, Gomez, Goncalves and Sampaio (2016) combined both James et al. (2005) and O'Donoghue (2005) techniques due to their large dataset, by using medians and 95% confidence intervals to display and compare performances of various athletes (James et al. (2005). In addition to this medians and quartiles were used to represent typical performances and their spread. All of the action variables were then transformed into standardised scores to allow for the construction of radar charts, which displayed profiles of players overall and according to positions (e.g. midfielder, forward, defender etc.). This study then progressed to analyse the variation of performances within-player match to match using the coefficient of variation for each match action and event. The differences were shown according to team and opposition quality and match location (Figure 2.4). However players that played less than two entire matches were excluded. Similarly, if the mean value of an action or event was 0 then it was treated as a missing sample. Magnitudes of clear differences were used and assessed according to (Batterham & Hopkins, 2006).

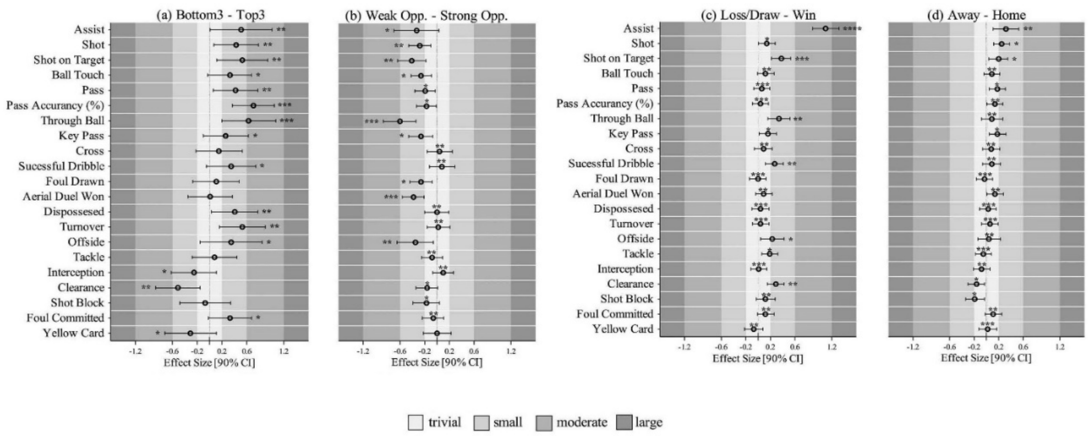


Figure 2.4. Displaying effect sizes of each match action or event of a) players from bottom3 and top3 team; b) players playing against bottom3 and top3 teams; c) players in lost/drawn games and in games won; d) players playing away and playing at home (Liu et al., 2016, p.7)

Table 2.4 Performance profiling literature Table

No.	Reference list	Sample	Reliability and Statistical Procedures	Main findings and Conclusion	Limitations reported	Suggestions for future research
1	Butterworth, A., O'Donoghue, P. & Cropley, B. (2013) 'Performance profiling in sports coaching: a review', *International Journal of Performance Analysis of Sport*, 13, pp. 572-593.	<u>*Qualitative*</u>	Review paper	• James et al. (2005) and O'Donoghue (2005) meet similar subset of criteria • Both methods could be extended to interpret individual performance by including situational variables • Form chart by James (2005) provides good visual information • Both methods do not utilise qualitative information • Selection of performance indicators is most important for profiling techniques	n/a	Coaching process, weighting opponents and key performance indicator – if these are applied correctly then will impact of performance profiling techniques
2	Eugster, M. J. (2012) 'Performance profiles based on archetypal athletes', *International Journal of Performance Analysis in Sport*, 12(1), pp. 166-187.	<u>*Matches*</u>: 441 players <u>*Competition*</u>: 2009/2010 NBA <u>*Sport*</u>: Basketball	Reliability: n/a Statistics: Archetypal analysis	• These profiles are based on archetypal athletes – not typical performances but extreme performances • Cluster based prototypes is very imprecise when profiling • Stage 1 is to estimate the archetypal athletes • Stage two is to identify and characterise the athletes as good and bad • Finally set all performers in relation to archetypes using a coefficients	n/a	Comparing archetypal analysis with other k-prototypes-like methods The a coefficients could be

				• Taj Gibson, Anthony Morrow and Kevin Durant considered as best basketball players of season		interpreted as compositional data
3	Hughes, M., Evans, S. & Wells, J. (2001) ‘Establishing normative profiles in performance analysis’, *International Journal of Performance Analysis in Sport*, 1(1), pp. 1-26.	<u>*Matches*</u>: <u>*Competition*</u>: <u>*Sport*</u>: Badminton and Squash (from other studies)	Reliability: T test Intra: 91.3-98.6% Inter: 91.3-98.6% Statistics: Chi square Dependent T tests Match descriptors	• To check for stability, calculations of percentage error and differences were determined • Frequencies of each variable were summated and means and std dev calculated • T-tests were used evaluate differences (badminton) • Data normalised (squash) • Cumulative means examined over series of matches and calculate percentage deviations for limits of errors	n/a	n/a
4	James, N., Mellalieu, S. & Jones, N. (2005) ‘The development of position-specific performance indicators in professional rugby union’, *Journal of Sports Sciences*, 23(1), pp. 63-72.	<u>*Matches*</u>: 22 <u>*Competition*</u>: 2001-2002 Professional Rugby Union Comp <u>*Sport*</u>: Rugby Union	<u>*Reliability*</u>: % errors <u>*Intra*</u>: 1.97±3.14% <u>*Inter*</u>:11.09±8.61 <u>*Statistics*</u>: Transformations Confidence limits Chi-square	• Significant differences were evident between individuals within all playing positions for principal performance indicators; passing, carrying and tackling for forwards, passing carrying tackling and kicking for the backs. • Intra-positional differences may occur due to variations in individual player’s style of play, the decision making demands of the position and the effects of independent variables.	• Operational definitions bias by expert panel	• Analyse ‘cleaning’ in rucks, driving in mauls and bridging at the breakdown • Whether a single profile for a position can be created or whether two or more are needed to

						account for independent variables.
5	Liu, H., Gómez, M., Gonçalves, B. & Sampaio, J. (2016) ‘Technical performance and match-to-match variation in elite football teams’, *Journal of Sports Sciences*, 34(6), pp. 509-518.	*Matches*: 496 *Competition*: 2008/09 to 2012-13 UEFA Champions League *Sport*: Soccer	*Reliability*: *Inter*: *Statistics*: ANOVA Independent Sample T Test k-means cluster analysis means, std dev, medians, IQR	• Grouped variables into scoring, attacking and passing and defensive variables • Games were separated according to whether they had balanced or unbalanced score difference. • Profiles according to team quality had significantly differing variables • Performance profiles changed according to team and opposition quality, match outcome and match location	Interactive effects of situational variables not interpreted Stage and period of competition may affect the result and performance	Interpret effect of situation variables Include stage and period of competition in analysis
6	Liu, H., Yi, Q., Giménez, J., Gómez, M. & Lago-Peñas, C. (2015) ‘Performance profiles of football teams in the UEFA Champions League considering situational efficiency’, *International Journal of Performance Analysis in Sport*, 15(1), pp. 371-390.	*Matches*: 380 *Competition*: 2012-2013 Spanish First Division Pro League *Sport:* Soccer	*Reliability*: n/a *Statistics*: Confidence limits Transformations Coefficient of variation	• Medians and confidence intervals to represent and compare performances • Medians and quartiles to represent typical performance and its spread • Data was transformed into standardised scores • Magnitudes were then assessed • Profiles were created taking into account team and opposition quality, match outcome and match location.	• Not included tactical variations • Data analysed as whole match, could have been split into halves or quarters	Include the independent variable competition stage
7	O'Donoghue, P. (2005) ‘Normative profiles of sports performance’, *International Journal of Performance*	*Matches*:564 *Competition*: 2002 Grand Slam	*Reliability*: n/a *Statistics*: Normalisation	• First stage is to determine normative performance percentiles in increments of 5% • Use multiple match data to determine mean and std dev for each indicator	n/a	n/a

	Analysis in Sport', 5(1), pp. 104-119.	Tournaments *Sport*: Tennis	means, std dev, medians, IQR	• Relate the performances to the normative data • Uses mean to represent typical performance – and IQR to represent variability about the mean performance		
8	Taylor, J., Mellalieu, S. & James, N. (2004) 'Behavioural comparisons of positional demands in professional soccer', *International Journal of Performance Analysis in Sport*, 4(1), pp. 81-97.	*Matches*: 22 *Competition*: British Professional soccer *Sport*: Soccer	*Reliability*: % error *Intra*: <5% *Inter*: <5% *Statistics*: Transformations Mean Chi square	• Significant differences in measured variables were evident between all four playing positions behavioural profiles • Intra positional profiles enable for individual players characteristics to become highlighted, significant differences were found between players in the same position.	• Using non parametric statistics Player had to play >5 matches to be included f	• Use alternative statistical methods to allow for post-hoc tests • Use qualitative methods to corroborate results
9	Vinson, D. & Peters, D. (2016) 'Position-specific performance indicators that discriminate between successful and unsuccessful teams in elite women's indoor field hockey: implications for coaching', *Journal of Sports Sciences*, 34(4), pp. 311-320.	*Matches*: 36 *Competition*: 2011-2012 England Womens Hockey Premier League *Sport:* Hockey	*Reliability*: Kappa >0.85 and agreements >90% *Statistics*: Transformations Confidence limits MANOVA	• Medians were calculated according to James et al. (2005) • Transformation of data into standardised z scores • MANOVAs were used to assess positional differences • Discriminant analysis was used to then predict finishing position based on variables. • Combined group centroid plots were used to display data	Sample only indicative of analysed national league and not others leagues	•

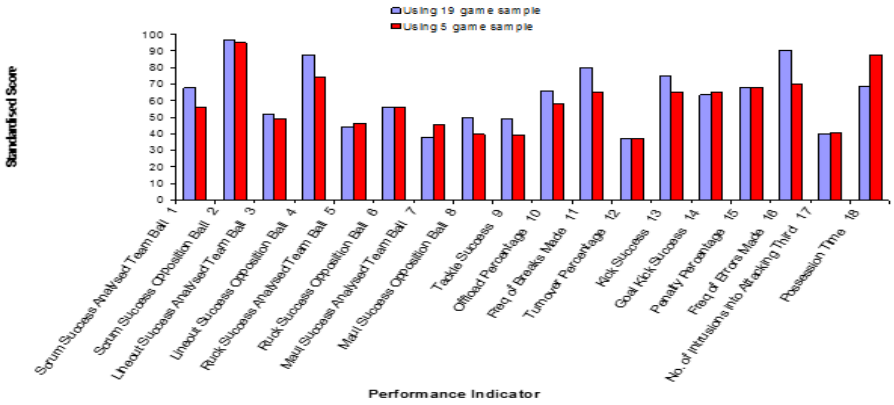
2.5 PREDICTING AND RATING PAPERS

2.5.1 BRACEWELL (2003) METHODS

Bracewell (2003) presented an objective method of quantifying individual player performances in rugby union to produce a player rating system, known as the Eagle Star Rating, which presents a single score of performance from a particular match. There are 15 players on a rugby union team allowed on the pitch during play, each of these players have differing roles and skills therefore it is important to analyse players according to their specific positions. Bracewell (2003) suggested that the overall contribution made to a team by an individual player must be taken into account to produce a relatively robust performance measure, therefore nine positional clusters were created. Bracewell (2003) used dimension reduction techniques (factor analysis) to reduce the amount of variables for analysis. This is important as some action variables are likely to be correlated to each other however this can be avoided by reducing the amount of variables to allow the same performance to be summarised with little loss of information. Factor analysis, using varimax rotation and principal component extraction, was performed on each positional cluster to identify and score the five groups of action variables (attack, possession, kicking, turnovers and defence) that best explained 60% of the variability in the data for each positional cluster. It is worth noting that all of the action variables contained within the groups had magnitudes >.05. Mahalanobis distance, which calculates how many standard deviations away a case is from the mean of a predictor variable (Field, 2009, p.789, was used to condense the five action variable groups' scores into a single score on a scale of 0-100, known as the Eagle rating. The score was focused around the philosophy that athletes aim for perfection therefore the score should reflect the distance from 'unattainable perfection' rather than using averages, whilst considering the combined impact of all action variables. If an individual score improves on a particular variable or its group, then the overall rating is improved and conversely the score is reduced if performance on ‘negative’ variables such as missed tackles and turnovers of possession are increased. This means that the referenced perfection point, is fixed and constant for all, allowing for fair comparisons to be made between players. Furthermore, the referenced perfection point is set far enough away so that there it cannot be exceeded. Form was also assessed in this method through the use of an exponentially weighted moving average and suggested that less than twenty matches be used when analysing form or consistency. Bracewell’s (2003) method was brief and had some portions missing due to commerciality agreements with Eagle Sports. A potential flaw in this rating system is that Bracewell (2003) made no adjustment for time spent on the field, so only the individual players’ contribution is considered with Bracewell (2003) acknowledging that the issue is highly debatable with coaches and players expressing differing opinions. Furthermore, James et al. (2005) transformed data for rugby union players that did not play the full match due to substation or injury to allow for comparisons to be made for the players against players that had played the whole game. However, Bracewell (2003) justify their approach of not accounting for time player by stating a conservative approach was chosen for the first iteration of the Eagle Star Rating. Finally, it was suggested that a team rating system should be created to assess the contribution of individual players’ performances to the overall team performance, which in turn can also be used to further refine the individual player rating system.

2.5.2 JONES ET AL. (2008) METHODS

Jones, James and Mellalieu (2008) developed a method of depicting team performances and form in professional rugby union through the use of standardising data and presenting the results in charts. A team's performance from twenty matches played during the 2002-2003 professional rugby union season were analysed. Performance indicators were combined to create percentages where possible to reduce the amount of variables being analysed with the authors stating that this would lead to a less complex depiction of performance. Jones et al. (2008) standardised the dataset by rescaling and centring the mean of a distribution at 0 and standard deviation of one. This allows for action variables of varying frequencies, to be analysed side-by-side giving a clear depiction of performance on the particular action variable or performance indicator. As the data was non-parametric the authors standardised the data using medians and the inter-quartile range. To assist the coaches who would be viewing the graphs, the authors multiplied the score by 15 and added 50 thereby creating a recognisable scale. The form charts were then constructed, with lines to indicate the median and interquartile range thereby allowing coaches to see how the team performed on the particular performance indicator in comparison to previous performances and the absolute limits for the percentiles were also included due to the variations found in the skewness values. The form chart was validated by the head coach of the analysed team who found that the "form chart provided a clear visual depiction of team performance" (Jones et al., 2008, p.694). A chart was constructed to compare the 20th match against the previous 19 and previous 5 matches (see Figure 2.5).



	Performance Indicator	Actual Match Value	Median	Median
1	Scrum Success Analysed Team Ball	100%	72.73%	84.62%
2	Scrum Success Opposition Ball	12.5%	0%	0%
3	Lineout Success Analysed Team Ball	70.59%	68.18%	71.43%
4	Lineout Success Opposition Ball	38.46%	7.14%	9.09%
5	Ruck Success Analysed Team Ball	88.24%	90.91%	89.29%
6	Ruck Success Opposition Ball	5%	3.85%	3.85%
7	Maul Success Analysed Team Ball	80%	100%	100%
8	Maul Success Opposition Ball	0%	0%	11.11%
9	Tackle Success	88.50%	88.89%	92.68%
10	Offload Percentage	43.75%	27.78%	21.43%
11	Freq of Breaks Made	15	7	7
12	Turnover Percentage	33.33%	63.64%	72.22%
13	Kick Success	84.21%	70.59%	73.81%
14	Goal Kick Success	90%	66.67%	57.14%
15	Penalty Percentage (Given Away)	27.27%	48.39%	52%
16	Freq of Errors Made	69	96	93
17	No. of Intrusions into Attacking Third	20	24	27
18	Possession Time	694 secs	509 secs	485 secs

Figure 2.5 Performance report of match 20 displaying standardised scores based on the previous 19 and 5 matches respectively, together with match 20 data and the median values of previous 19 and 5 matches (Jones et al., 2008, p.695).

Figure 2.5 shows the standardised scores in a graph and below a Table containing the actual value of the 20th match, and medians of the previous 19 games and 5 games is shown, future papers should follow this methodology as it puts the standardised scores into context to the actual values and medians achieved. A way of improving this study could be to try and incorporate performance reports that account for independent variables such as team and opposition quality and match location which could give meaningful information for the readers, coaches and performance analysts.

2.5.3 ROBERTSON AND JOYCE (2015) METHODS

Robertson and Joyce (2015) created a match difficulty index (MDI) for the Super Rugby competition that took into account the effects of numerous independent variables to enable teams to better plan and prepare for matches. Three hundred and forty nine matches from the 2011 to 2013 Super Rugby competitions were included for analysis. Six predictors of match difficulty included were, opposition rank previous year, opposition rank current year, time zone difference, between match break, match location and distance travelled. However, due to multicollinearity issues distance travelled was removed as a predictor as it correlated with time zone difference. Binary logistic regression was utilised to develop models using the five remaining independent variable predictors with the dependent variables being win or loss therefore the matches that resulted in draws were removed from the dataset (n=24). Regression analysis predicted probability outputs from the models with the results being used to calculate the MDI for each match by subtracting 1 from the logit probability value of win and multiplying 10, enabling a scale of 0-10 to be created. The model that explained the best explanation of performance with the least amount of variables (parsimonious model) was subjected to cross-validation to assess the generalisability of the results. Three models were created from the logistic regression, Model 1 was able to predict match outcome for Super rugby matches played during the 2011 and 2012 seasons through the five independent variables. This model found that as the rank of the opponent for both current and previous season increased (i.e. lower down the league Table) the logit probability of winning a match also improved. However this probability was reduced for sides not playing at home, when there were shorter between match breaks, and when having greater time zone changes from one week to the next. Model 2 only included significant predictors from Model 1 by removing time zone difference and between match break, similar results were found to Model 1 with the percentage of correct predictions being similar (~66%), also opposition rank current year, opposition rank previous year and match location were all significant. Model 3 removed the predictor opposition rank current year, resulting in a slight reduction in overall fit compared to Model 1 and 2. Cross validation of models were undertaken with all three models fitting the 2013 data slightly better than the original sample and similarly for correct predictions which increased by ~5%. The study suggested that opposition rank from both current and previous year and match location are the independent variables that best determine the match outcome and therefore difficulty. The difficulty of matches increased noticeably when teams had to travel internationally and to a lesser extent when travelling nationally compared to when playing at home. Perhaps the authors could have included the data from matches that resulted in draws, by excluding this data the authors lost ~7% of the dataset, to avoid this they could have classified match outcome as win and not win (incorporating both loss and draws) instead. The authors also state that this methodology could be adapted to create a difficulty index for other sports.

2.5.4 HARROP AND NEVILL (2014) METHODS

Harrop and Nevill (2014) identified performance indicators that predicted success in an English professional league one soccer team and identified performance indicators that discriminated between wins, draws and losses. Forty six matches played by an English League one soccer team during the 2012-2013 season were included in the analysis. Variables were put into three categories, offence, defence and independent variables. Some variables were identified as being not normally distributed therefore descriptive data were presented using medians and inter quartile ranges. A Kruskal

Wallis test was performed in the first part of the study to identify performance indicators that discriminated between the three match outcomes, and a binary logistic regression with backwards elimination was used in the second part of the study to identify performance indicators that best predicted match outcome. The Kruskal-Wallis identified significant differences for the variables relating to offence, passes, percentage of successful passes completed and passes made in opposition half. The results also indicated that significantly more passes were made when the team lost compared to when they won and drew ($p<0.001$), however, no differences were evident for passes made when drawing and winning games ($p=0.235$). Significantly lower percentages of successful passes were found for teams that drew compared to when they won ($p<0.01$) and lost ($p<0.001$). Significantly more passes were made in the opposition half when the team lost in comparison to when they won ($p=0.039$) and drew ($p=0.039$). No significant differences were found for the variables relating to defence ($p>0.05$). The final model from the logistic regression analysis identified that fewer passes, more successful percentage of passes, more shots, fewer dribbles and match location were significant factors ($p<0.05$) that correctly predicted match outcome in 71.7% of games. This paper could have been improved by including a larger sample size that was more indicative of performance over the season. Furthermore, although performance indicators were identified for this particular team, without information about the quality of the analysed team such as where they finished in that season, it is hard to make a judgement on how useful the results are for other teams in the league. Another interesting question this paper could have included was whether performance indicators varied according to the quality of the opponent. Finally, including variables that directly relate to success like shots and conversions etc., will clearly be linked to winning therefore the inclusion of variables related to scoring points does not give any meaningful information. Therefore studies should exclude spurious variables related to points scoring to enable more meaningful information to be obtained and enable investigations into other variables that may lead to success which may be excluded otherwise if these variables are included.

Table 2.5 Predicting and rating literature Table

No.	Reference list	Sample	Reliability and Statistical Procedures	Main findings and Conclusion	Limitations reported	Suggestions for future research
1	Bracewell, P. (2003) 'Monitoring meaningful rugby ratings', *Journal of Sports Sciences*, 21(8), pp. 611-620.	*Qualitative Matches*: unclear *Competition*: *Sport*: Rugby union	*Statistics*: Factor analysis with Principal Component extraction Multivariate distance measure	• 9 positional clusters were identified • Factor analysis was then used to identify five factors for each cluster which explained more than 60% of variability in data. • Multivariate distance measure condenses the five factor scores into a single performance measure	• No adjustment for time spent on the field	• Create a team rating system
2	Boulier, B. & Stekler, H. (2003) 'Predicting the outcomes of National Football League games', *International Journal of Forecasting*, 19(2), pp. 257-270.	*Matches*: 1212 *Competition*: 1994-2000 NBA *Sport*: Basketball	*Reliability*: n/a *Statistics*: Spearman's rank correlations coefficients Poisson regression Brier score Logit regression	• Used betting markets predictions • New York Times rankings were compared to other ranking systems and correlation coefficients ranged from 0.83-0.97 • Forecasts based on power scored predicted outcomes 60% of the time	• Used limited data from each season – that particular portion of the season may not be indicative of whole season	•

				• Higher ranked teams were more likely to win when playing at home		
3	Constantinou, A., Fenton, N. & Neil, M. (2012) ‘pi-football: A Bayesian network model for forecasting Association Football match outcomes’, *Knowledge-Based Systems*, 36, pp. 322-339.	<u>*Matches*</u>: 380 <u>*Competition*</u>: 2010/2011 English Premier League <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Bayesian Network Model Rank of probability score	• Team names were replaced with team strength ratings for the particular team in the respective seasons. • The model generates predictions for matches by considering strength, form psychology and fatigue and match location. • The accuracy of objective forecasts was sig inferior to bookmakers forecasts however the use of subjective information improved forecasting capability significantly • This model won ~35% of bets	• n/a	• n/a
4	Goddard, J. (2005) ‘Regression models for forecasting goals and match results in association football’, *International Journal of forecasting*, 21(2), pp. 331-340.	<u>*Matches*</u>: unclear <u>*Competition*</u>: 1992-1993 to 2001-2002 English Premier League <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Poisson regression Probit regression	• Data from home teams recent performance are more useful than its recent away performance • Similarly away teams recent away performance is more useful than its recent home performance • Best forecasting is achieved by using a hybrid model combining a results-based	• n/a	• n/a

				variable with goals-based performance co-variates		
5	Graham, J. & Mayberry, J. (2014) 'Measures of tactical efficiency in water polo', *Journal of Quantitative Analysis in Sports*, 10(1), pp. 67-79	<u>*Matches*</u>: 45 <u>*Competition*</u>: 2011 European Championships & Qualifying rounds, 2012 Dublin Cup and 2012 London Olympics <u>*Sport*</u>: Elite Men's Water Polo	<u>*Reliability*</u>: n/a <u>*Statistics*</u>: Wilcoxon signed rank tests Mann Whitney U Conditional Binomial tests Chi square	• Efficiency rating was created for the probability of a tactic resulting in a direct goal or indirect goal. • Overall distribution of goals by tactics were similar for winning and losing teams • Winning edge cannot be explained by play distribution – teams use similar strategies • Winning teams have a higher turnover rate of 38% and converted 18% more power play tactics than losing teams	• Only analysed offensive tactics	• Analyse defensiv e tactics
6	Harrop, K. & Nevill, A. (2014) 'Performance indicators that predict success in an English professional League One soccer team', *International Journal of Performance Analysis in Sport*, 14(3), pp. 907-920.	<u>*Matches*</u>: 46 <u>*Competition*</u>: 2012 English League 1 <u>*Sport*</u>: Soccer	<u>*Reliability*</u>: Kappa <u>*Inter*</u>: .990-.979 <u>*Statistics*</u>: Kruskal Wallis Binary Logistic Regression	• Significant differences were evident for number of passes, percentage of successful passes, and passes made in the oppositions half • Significant more passes and passes in the oppositions half were made when teams lost compared to when winning and drawing. • Regression revealed that teams should perform fewer passes and dribbles but complete more successful	• Only analysed 1 team – may not be indicative of all teams • Did not account for match status	• Use indepen dent variable s • Analyse future seasons for perform ance profilin g • Look at

				passes and shots to be successful		defensive variables
7	Jones, N., James, N. & Mellalieu, S. (2008) ‘An objective method for depicting team performance in elite professional rugby union’, *Journal of Sports Sciences*, 26(7), pp. 691-700.	*Matches*: 20 *Competition*: 2002-2003 European professional team *Sport*: Rugby Union	*Reliability*: % error Inter: <5% *Statistics*: Linear Transformations	• Performance indicators were qualitatively identified by authors and validated by coaches and were then also presented as percentages to reduce the number of PI’s • Medians were used when standardising the indicators • Current form was investigated by using the last 5 matches and previous form as the previous seasons 19 matches • Form charts revealed that both teams performed most indicators at similar levels to their previous 5 matches	• Small sample size •	• The effect of sample size used when standardising needs investigating • Investigate the use of current form • Further research to explore other potential analysis mechanisms

8	Mertz, J., Hoover, D.L., Burke, J.M., Bellar, D., Jones, L.M., Leitzelar, B. and Judge, L.W. (2016) 'Ranking the Greatest NBA Players: A Sport Metrics Analysis', *International Journal of Performance Analysis in Sport*, *16*(3), pp. 737-759.	<u>*Matches*</u>: Unclear <u>*Competition*</u>: NBA <u>*Sport*</u>: Basketball	<u>*Reliability*</u>: None <u>*Statistics*</u>: <u>*Multiple linear regression*</u>	• Winning may not be the most important factor when ranking all-time greatest players • Whilst winning NBA championships increased players' rankings, average points scored per game during career, average rebounds recorded per game during career and average assists recorded per game during career (APG). • APG most important to increase ranking	• Information bias • The ranking of players assumed there was equal gaps in ability between adjacently ranked players • Model 2 based solely on offensive statistics	• Defensive variables should be considered for inclusion in future models • Consider points per possession as an independent variable
9	Ofoghi, B., Zeleznikow, J., Macmahon, C., Rehula, J. and Dwyer, D.B. (2016) 'Performance analysis and prediction in triathlon', *Journal of Sports Sciences*, *34*(7), pp. 607-612.	<u>*Matches*</u>: Unclear <u>*Competition*</u>: The official Triathlon World Championship and World Championship Series, World Cup and Olympic	<u>*Reliability*</u>: None <u>*Statistics*</u>: <u>*Bayesian Networks*</u>	• Bayesian network analysis revealed performance patterns in five key areas of triathlon (3 race legs and 2 transitions). • Complex relationships were identified between each component of the triathlon and performers overall race performance	• None reported	• None reported

		Games competition				
		Sport: Triathlon				
10	Robertson, S. & Joyce, D. (2015) ‘Informing in-season tactical periodisation in team sport: development of a match difficulty index for Super Rugby’, *Journal of Sports Sciences*, 33(1), pp. 99-107.	*Matches*: 349 *Competition*: 2011-2013 Super Rugby seasons *Sport*: Rugby Union	*Reliability*: n/a *Statistics*: Logistic regression 2 way ANOVA Spearmans R	• Developed a match difficulty rating utilising independent variables • Opposition ladder position and match location having greatest influence on match difficulty • Three models were constructed with match outcome correctly classified 66.25, 65.5% and 63.7% by the respective models	• Only 3 seasons of data utilised • Possible further independent variables to include	• Develop MDI for other sports using similar method ology
11	Scholes, R. & Shafizadeh, M. (2014) ‘Prediction of successful performance from fielding indicators in cricket: Champions League T20 tournament’, *Sports Technology*, pp. 1-7.	*Matches*: 17 *Competition*:2012 Champions League T20 Competition *Sport*: Twenty20 Cricket	*Reliability*: n/a *Statistics*: Step wise discriminant analysis	• Fielding indicators were significant predictors of match outcome • Catches inside the 30yd circle and outside the 30 yard circle were also significant predictors of match outcome • Winning teams had higher success for catching inside the 30yard circle (89.13%) and for return throws inside the 30yd circle (70.15%) • Outside the 30yd circle winning teams have higher success in catching (84.78%)	• Small sample size • No reliability testing	• Future research in fielding needed

Ziv, G., Lidor, R. & Arnon, M. (2010) 'Predicting team rankings in basketball: The questionable use of on-court performance statistics', *International Journal of Performance Analysis in Sport*, 10(2), pp. 103-114.	*Matches*: *Competition*: 2002-2003 to 2008-2009 Israel IBSL League *Sport*: Basketball	*Reliability*: n/a *Statistics*: Step-wise multiple regression Factor analysis	• Factor analysis enabled 12 variables to be condensed to 6 • Absolute variables were converted into z-scores • Number of statistics do not reliably predict final team rankings • The variable SCORE was a predictor in combined data of all seasons	• n/a	• n/a

2.6. CONCLUSION

In summary, this literature review has identified strengths and areas for improvement across the performance indicator, profiling and predicting and rating literature included in this review. PI research has several areas that authors need to use appropriate definitions, sample sizes, and independent variables for future research. The PI definitions proposed by this review will allow coaches and performance analysts to clearly understand the different performance variables according to their importance and influence on success. This may help to bridge the academic and applied gap that sometimes exists in performance analysis research. Furthermore, the use of independent variables has been shown to be important, with many papers failing to include these important variables that give context to their findings. For example, opposition quality enables the identification of whether teams play differently according to whether their opposition is ranked as high or low quality. However, the definitions of team and opposition quality need to be defined and developed appropriately in forthcoming papers, as independent variables have been shown to influence match outcome. Furthermore, analysing teams according to whether they won or lost the match may not give as much meaningful information as using point's difference. For example it can be established whether performances on certain variables can lead to a higher or lower points difference, clearly this is more meaningful than using match outcome alone. Profiling methodologies can be improved by utilising independent variables as shown by Liu et al. (2015), however the data must be normalised and displayed appropriately in order to make fair comparisons.

CHAPTER 3: DEVELOPING TEAM PERFORMANCE INDICATORS THAT BEST PREDICT MATCH OUTCOME IN PROFESSIONAL RUGBY LEAGUE

3.1 INTRODUCTION

Professional sport has progressively become more business-like with increased analysis and scrutiny of team and player performances, particularly in the media and by coaching staff (Abreu, Moura, Silva, Reis & Garganta, 2011; Bull, Shambrook, James & Brooks, 2005; Golby & Sheard, 2004). Consequently, sports science support has grown, including the provision of performance analysis, which is an integral part of the coaching process (Carling, Williams, & Reilly, 2005; Groom, Cushion, & Nelson, 2011; Mackenzie and Cushion, 2013). Performance analysis is predominantly an objective, quantitative method for understanding and improving performance of both individuals and teams (Drust, 2010; Gabbett, 2005; Glazier 2010; Hughes & Bartlett, 2002; Hughes & Franks 2004; Thomson, Lamb & Nicholas, 2013).

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 (Reep & Benjamin, 1968). Cupples and O’Connor (2011) determined position specific PIs in Australian elite youth rugby league using the Delphi method involving 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 differential data 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) also advocated this method for preparing for matches by including the opposition in the analysis; it is more common for papers to have used absolute values however (Higham, Hopkins, Pyne & Anson, 2014b; Lago-Penas, Lago-Ballesteros & Rey, 2011; Villarejo, Palao, Ortega, Gomez-Ruano & Kraak, 2015).

Whilst Hughes and Bartlett's (2002) definition of a PI has been widely viewed (17,532 views on Journal of Sports Sciences website, 18/07/2017) and cited (775 citations, Google Scholar website, 18/07/2017) it appears that definitions of success have been interpreted differently. Action variables have been described as PIs when they had not been shown to be indicative of success (Campos, Stanganelli, Campos, Pasquarelli & Gomez, 2014; Carroll, 2013; Castellano & Casamichana, 2015; Castellano, Casamichana & Lago 2012; Higham, Hopkins, Pyne & Anson, 2014a; Kajmovic, Kapur, Radjo, & Mekic, 2014; Lago-Penas, Lago-Ballesteros & Rey, 2011;

Meletakos, Vagenas & Bavios, 2011; Najdan, Robins & Glazier, 2014; Robertson, Back & Bartlett, 2016; Robertson, Gupta & McIntosh, 2016; Scholes & Shafizadeh, 2014; Vahed, Kraak & Venter, 2014; Villarejo, Palao, Ortega, Gomez-Ruano & Kraak, 2015), when not significantly related to success (Graham & Mayberry, 2014; Higham, Hopkins, Anson & Pyne, 2014b) or significant indicators of success were referred to as key performance indicators (O'Donoghue, 2008). Similarly, key or principal PIs were named without clear definitions of what these terms meant (Bremner, Robinson & Williams, 2013; Butterworth & O'Donoghue, 2013; Najdan, Robins & Glazier, 2014; Shafizadeh, Taylor & Penas, 2013). For clarity this thesis will consider performance variables as being either 1) an action variable i.e. a variable that has not be shown to be indicative of successful performance; 2) a PI, a variable that is statistically indicative of successful or unsuccessful performance (correlation coefficient between 0.3-0.5, effect size 0.5-0.8, or $p<.05$); or 3) a key PI, a variable that is more strongly associated with successful or unsuccessful performances than other PIs (correlation coefficient >0.5, effect size >0.8, or $p<.001$). These criteria could be modified according to the statistical approach used although justifications for criteria should be presented. This approach would make it easier for academics and practitioners to understand and interpret the effects of PIs on performance.

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. Other similar measures could include 1) Recent form as assessed by performance over the past 5 games (ratio), 2) recent form assessed by cumulative league points gained from the beginning of the season (ratio) and finally, 3) Historical form using the average league position from the past three seasons (ordinal). Finally, scoring first has been shown to significantly improve team's chances of winning in hockey (Jones, 2009), basketball (Courneya, 1990), and soccer (Garcia-Rubio, Gomez, Lago-Penas & Ibanez, 2015; Pratas, Volossovitch & Carita, 2016). This has not been investigated in rugby league and should be included in a future study.

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. The final points difference has been used in past research 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 to assess their relative worth in providing meaningful performance information.

3.2 METHODS

3.2.1 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. All methodologies were evaluated, amended and validated using elite coach feedback (n=2). Ethical approval was granted by a University Ethics Sub-Committee (see Appendix 3.1 & 5.1).

3.2.2 FORM VARIABLES

Team and opposition quality was assessed using 5 measures of form (Table 3.1) using either points gained or final league positions (Appendix 3.2). Where lower values equated to better performance (all league position variables) the values were reverse scored i.e. away score minus home score, to ensure positive values always equated to success.

Table 3.1. Definitions of form (team and opposition quality)

Form	Year / Matches
5 game form	Points gained in previous 5 games
Cumulative league form	Points gained during current season
Current season final league position	End of current season league position
Previous season final league position	Previous season league position
Average of past 3 season's league positions	Average past 3 seasons

3.2.3 ACTION VARIABLES

Variables were made relative by subtracting the away team performance from the home team. Hence positive values resulted when the home team outperformed the away and negative for the opposite. Field (2009, p.212) suggested that there should be some rationale for the inclusion of variables into a regression analysis and hence correlation coefficients were calculated for each variable in relation to point's difference. These were interpreted according to Cohen (1992) as being 0.1 (small effect size), 0.3 (medium effect size) and 0.5 (large effect size).

Twenty-four variables had correlations >0.3: 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 (Appendix 3.3).

Collinearity diagnostics were performed to remove variables that had high multicollinearity. Field (2009) suggests that tolerance values should be <1, and variance inflation factor (VIF) values >10 should be removed. Variables removed were plays (VIF= 125.24), total sets (VIF= 19.78), tackle busts (VIF= 116.70) and play the ball (VIF= 88.53) resulting in 20 action variables.

3.2.4 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. Cross-validation, using the 2014 data; a data splitting method, following the guidelines of Field (2009, p.222), assessed the fit of each model. Finally, an exhaustive CHAID decision tree was grown using win/loss as the binary response variables.

3.3 RESULTS

3.3.1 MODEL 1 - LOGISTIC REGRESSION

Backwards LR logistic regression removed the least important variables sequentially based on the likelihood-ratio for each variable (Field 2009, p.272). The final (parsimonious) model (Table 3.2) retained 11 relative action variables in the model which could correctly classify match outcome 91% of the time.

The results showed that if the home team scored first then the likelihood of winning was 74.4% (OR=2.9). Conversely, finishing the previous season one position lower than an opponent equated to a probability of winning of 44.0% (OR=0.9).

Table 3.2. Model 1 - Relative Performance indicators that best predict match outcome (win/loss) in rugby league

Variables	β (SE)	OR	95% CI		Probability
			LB	UB	
(Constant)	-0.6 (0.4)	0.6			
Score First	1.1 (0.5)*	2.9	1.2	7.1	74.4%
Completed Sets	0.5 (0.1)***	1.6	1.4	1.8	61.0%
Current season final league position	0.2 (0.1)**	1.2	1.1	1.4	54.3%
Successful Collections	0.1 (0.1)	1.1	1.0	1.2	52.0%
Dominant Carry	0.1 (0.0)	1.1	1.0	1.2	51.7%
Metres Gained	0.0 (0.0)***	1.0	1.0	1.0	50.2%
Scoot Metres	0.0 (0.0)*	1.0	1.0	1.0	50.2%
Time in Possession	0.0 (0.0)*	1.0	1.0	1.0	49.8%
Successful Pass	0.0 (0.0)**	1.0	1.0	1.0	48.7%
Scoot	-0.1 (0.0)**	0.9	0.8	1.0	44.7%
Previous season final league position	-0.1 (0.1)*	0.9	0.8	1.0	44.0%

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

When the 2014 data was used to cross-validate the model using the 11 variables (Appendix 3.4), match outcome was correctly classified 92.2% of the time (Table 3.3), a slight increase from 91.0% (Appendix 3.5).

Table 3.3. Cross-validation of the 2012 & 2013 relative variable logistic regression model against the 2014 data

Model Dataset	-2 Log Likelihood	Nagelkerke R^2	Model % Correct Match Classification
2012 & 2013	142.4	0.84	91.0%
2014	64.5	0.84	92.2%

3.3.1.1 DATA CHECKING

Standardized residuals were analysed to ensure no bias in the model, with 2.47% of cases outside of the ±1.96 limits and 0.82% of cases had values outside the ±2.58 limits, which was deemed acceptable (Field, 2009, p.293). However, 4 cases (Table 3.4) were investigated for having residual values >3 (Field, 2009, p.293). VIF (<5.14) and Tolerance levels (>.83) did not indicate any collinearity issues (Field (2009, p.242). Cooks distances were analysed to ensure values were <1 (Field, 2009, p.293) with one case highlighted, this case was the same as one of the cases highlighted in the residual analysis and was therefore not excluded. Finally, Leverage and DFBeta values were analysed, all were <1, which indicated no causes for concern (Field, 2009, p.293).

3.3.1.2 RESIDUAL ANALYSIS

Four outliers were identified in the residual analysis for analysis (Table 3.4). Outlier 1 was incorrectly identified as a loss for the home team by the regression model. The variables (previous season final league position, score first, possession, metres gained, successful passes, scoots & scoot metres) had values which the model considered as representative of a match loss. Only two variables (current season final league position and completed sets) had values consistent with a match win, whilst two (dominant carries and successful collections) had 95% CI's which had a lower boundary <1 and an upper boundary >1 and were therefore deemed unreliable (Field, 2009).

Table 3.4. Table analysing the 4 main outliers from Model 1 – Logistic regression

	Expected	Outlier 1	Outlier 2	Outlier 3	Outlier 4
Case		40	79	106	239
Match outcome	Win	Win (1 pt)	Win (16 pts)	Win (4 pts)	Win (1 pt)
Predicted outcome	Win	Lose	Lose	Lose	Lose
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: Expected is what the logistic regression model expects the values to be in order to be classified as a win. – indicates that the regression model expects a negative value, + indicates that the regression model expects a positive value, * indicates that the Beta coefficients confidence intervals did not display a reliable value.

3.3.2 MODEL 2 - 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 10 relative action variables (Table 3.5).

Table 3.5. Model 2 - Performance indicators that best predict points difference

	2012 & 2013 Dataset $R^2 = 0.865$			2014 Dataset $R^2 = 0.874$		
Variables	**β (SE)**	**β CI**		**β (SE)**	**β CI**	
		LB	**UB**		**LB**	**UB**
(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, CI is confidence intervals, LB is CI lower boundary and UB is CI upper boundary. *p<.05, **p<.01, ***p<.001.

which could explain 86.5% of variance 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 differential by 1.2 points. Conversely, increasing the home teams relative scoot count decreased the point's differential by 0.2 points.

3.3.2.1 DATA CHECKING

Standardized residuals were analysed to ensure no bias in the model, with 5.21% of cases outside of the ±1.96 limits and 0.55% of cases had values outside the ±2.58 limits, which was deemed acceptable (Field, 2009, p.293). VIF (<4.70) and Tolerance levels (>.21) did not indicate any collinearity issues (Field (2009, p.242). Cooks distances were analysed to ensure values were <1 (Field, 2009, p.293. Finally, Leverage and DFBeta values were analysed, all were <1, which indicated no causes for concern (Field, 2009, p.293).

3.3.3 SUMMARY OF THE REGRESSION MODELS

Prior to all regression analyses, variables were identified for inclusion based on correlation coefficients with points difference, variables with coefficients >.3 were identified as PIs and, >.6 as KPIs. Post regression analysis, variables were classified as KPI's for linear regression if it had a β value >1 and for logistic regression if it had a probability of winning > 60%. Otherwise all variables left were deemed PI's as they remained in the final models. Two KPIs and Fourteen PIs were identified from the logistic and linear regression models and presented in Table 3.6, alongside their respective effects on success if there was a one unit increase i.e. probability of winning calculated from odds ratio (logistic regression) and how many points would be added to the final points difference (beta coefficient, linear regression).

Table 3.6. List of PIs and KPIs identified by the linear and logistic and their effects on success

Variables	Logistic Backwards			Linear Backwards			PI/ KPI
	OR	95% CI		β	95% CI		
		LB	UB		LB	UB	
Score first	2.9	1.2	7.1	2.4	0.4	4.5	KPI
Completed Sets	1.6	1.4	1.8	1.2	1.0	1.4	KPI
Current season final league position	1.2	1.0	1.3	0.6	0.3	0.9	PI
Successful collections	1.1	1.0	1.2				PI
Dominant carry	1.1	1.0	1.2				PI
Metres gained	1.0	1.0	1.0	0.0	0.0	0.0	PI
Scoot metres	1.0	1.0	1.0				PI
Time in possession	1.0	1.0	1.0				PI
Successful Pass	1.0	1.0	1.0				PI
Scoot	0.9	0.8	1.0	-0.2	-0.3	-0.1	PI
Previous season final league position	0.9	0.8	1.0				PI
Breaks				0.9	0.6	1.3	PI
Supported Break				0.4	-0.1	0.8	PI
Unsuccessful pass				0.4	0.1	0.6	PI
Total passes				-0.1	-0.1	-0.1	PI
Cumulative league form				-0.2	-0.4	0.0	PI

Note: OR is Odds ratio, 95% CI is 95% confidence intervals, LB is lower boundary of CI and UB is upper boundary of CI, β is the unstandardized beta coefficient. PI are determined by β <1 or win probability <60%, KPI determined by β >1 or win probability >60%. All variables correlation coefficients were significant at $p < 0.001$.

3.3.4 MODEL 3. EXHAUSTIVE CHI-SQUARE AUTOMATIC INTERACTION DETECTION DECISION TREES

A machine learning (data mining) technique was adopted to create a decision tree model that could best predict winning and losing (Figure 3.1) from a training sample of 75%, and cross-validated against a test sample of 25% of the data. The decision tree identified the most important variable as metres gained, followed by completed sets and first carry metres. Specifically, the tree explained that when the home team outperformed their opponents by 260 or more metres they won 97.5% of the time, dropping to 2.5% when the home team underperformed by more than 259 metres. When home teams performed in-between these values they were only 60.9% likely to win, although this rose to 78% if they matched or outperformed on the amount of completed sets, and finally it rose again to 91.8% if the home team outperformed the opponents by 25 or more first carry metres.

The training sample (Appendix 3.6) could correctly classify 85.4% of games and the cross-validation revealed that it could classify 85.5% of games correctly from the test sample (Table 3.7).

Table 3.7. Classification Table for the training (75%) and test (25%) samples.

Sample	**Observed**	**Predicted**		**Percent Correct**	**Overall % correct**
		Loss	**Win**		
Training	Loss	131	90	81.4%	85.4%
	Win	29	215	88.1%	
Test	Loss	49	14	77.8%	85.5%
	Win	7	70	90.9%	

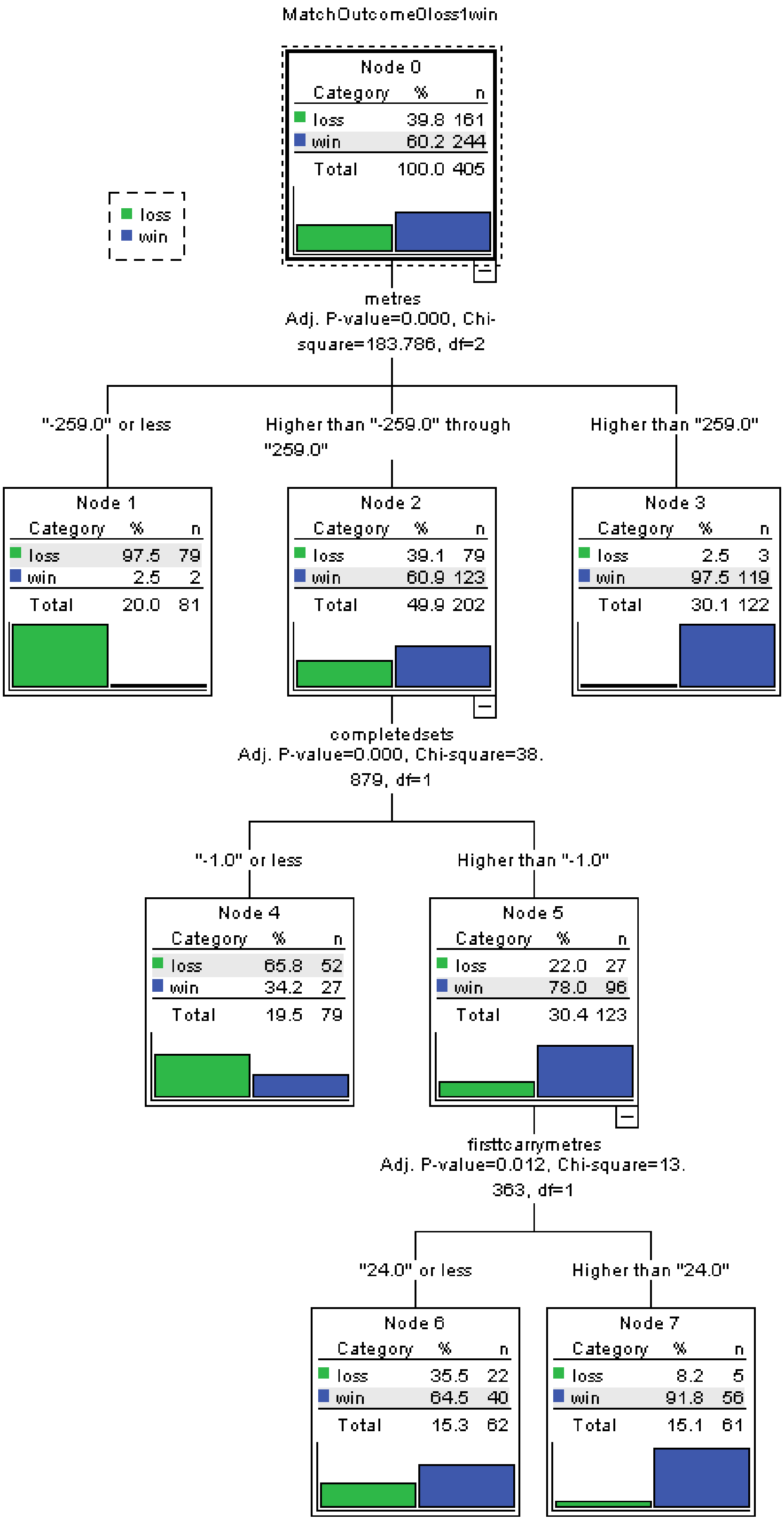


Figure 3.1. Exhaustive CHAID interaction trees from the training sample (75%).

3.4 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. When conducting sporting performance research, the aim should be for practitioners to be able to utilise the results to improve sporting performance. This process is hindered through irrelevant investigations and unclear methodologies that make it difficult to understand what the authors have actually done. This issue is prevalent in performance indicator research where unclear definitions of PIs make it difficult to understand why the authors have deemed the performance variables to be performance indicators in the first instance. Furthermore, a lack of contextual information when analysing a team's variables can provide misleading account of performance (cf. Hughes and Bartlett, 2002) as often these analyses did not take into consideration performance on the same variables by the opponent. To address this issue, this study aimed to allow a) replication by academics or practitioners by using clear definitions and methods, b) produce results that can be utilised by coaches, players and performance analysts to help improve their performances, c) provide context by making the data relative to the opponent.

This study utilised three statistical tests to provide a robust analysis of performance variables and enable the identification of PIs by considering success according to whether a team won or lost (logistic regression and machine learning) and the point's differential between home and away teams (linear regression). These two dependent variables are comparable but different as match outcome simply tells us whether a team won or lost (dichotomous variable), whereas points difference is a scaled variable that describes whether a team won (positive values) or lost (negative) and by what margin. When comparing the final logistic and linear models, it was apparent that they loaded on 5 common variables with 5 unique to both. Further investigations are required to determine the reasons for these differences and to determine whether one approach is more suitable for this type of analysis.

Regression analyses provided detailed results which were not straight forward to understand, particularly for coaches and players without sophisticated statistical expertise. One such complication is the fact that stepwise methods remove (or do not add) variables that do not add to the prediction of the dependent variable after another variable that has a higher prediction ability has already been added to the model. An example of this was seen when analysing breaks, which 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. Similarly, cumulative league form was removed from the logistic regression as the model had retained current season and previous season final league position. Therefore, whilst cumulative league form can be a predictor of match outcome the regression analyses identified that other indicators of form were better predictors. It is thus contended that the goal of regression to minimise the number of explanatory variables in a model is both a strength and weakness. A reduced number of variables has the advantage of being simple and can help identify the most important variables from a large number of potentially less useful ones. However, this reductionist method can also give a misleading account of which variables are 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 the reductionist approach i.e. minimising the number of components necessary to explain the variability of a dependent variable, whilst retaining the complexity inherent when a large number of variables are being considered.

The complexity of the regression model is often considered simply from the point of view of the prediction equation which can be understood in terms of how a one unit increase in a variable, assuming all other variables do not change, affects the dependent variable. This attempt at simplifying a complex relationship has some drawbacks. First of all consider variables that are frequently performed e.g. metres gained. As an invasion sport, rugby league involves teams needing to gain metres forward to have a chance of scoring. Not surprisingly, Gabbett (2014) found that semi-professional rugby league teams in Australia who finished higher in the league had gained more metres than those lower down. Clearly, metres gained was related to success, as the main mode of scoring points is by scoring tries which requires gaining metres. The regression models indicated that gaining an additional metre would result in negligible changes to match outcome and points difference. However, winning teams often gained in excess of 260 metres more than their opponents. The interpretation of the effect of a unit change in metres gained is not, unfortunately, a simple multiplication of the probability that the dependent variable will change by say 260. This is because the probability of changing the outcome (match outcome or points difference) changes depending on the value of the metres gained variable. In other words a unit gain in metres gained may increase the probability of winning the match more for instances when a team had gained less metres 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 is practically not sensible.

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 scoring first would not be as important a factor in determining whether a team won or lost. However, the regression results showed this variable to be the most important indicating scoring first does increase 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. To explain this, it is logical to expect that within a large sample of matches, there would be instances of matches won easily by a superior team who would inevitably score first and win (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%). Consequently, when interpreting the 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. This recommendation is similar to the old adage "a mean is meaningless without a standard deviation" as the beta coefficient and odds ratio values presented in the regression output are fairly meaningless values associated with just a small portion of the overall data set.

The analysis of residuals from the logistic regression model highlighted performances which the regression model was unable to correctly predict. These cases were investigated to determine whether the data was erroneous and the case excluded to improve the predictive ability of the model. The four games incorrectly predicted as losses were due to unexpected performance on several variables. For example, for outlier 3 the team had not scored first and had been outperformed on completed sets, metres gained and scoot metres, all of which would suggest a match loss whereas the match has been won. However, these circumstances did not warrant the case being excluded as the data was an accurate, albeit unusual, occurrence, reflecting the unpredictable nature of some sports. Hence despite being outperformed on variables identified as typically consistent with winning matches, teams can still win even if it is by just 1 point, as was the case with this game. This highlights the complex nature of sporting performance, demonstrated here in rugby league, which suggests that the only variable which guarantees success is scoring more points than the opposition, but this is both obvious and unhelpful.

The regression analyses also produced unexpected, or counterintuitive, results. For example, having more time in possession was found to slightly reduce a team's chance of winning (CI = 0.99 – 1.00). This is illogical although the actual probability was so close to 50% as to be most likely a sampling issue rather than a genuine effect. Indeed, many of the variables in the regression results had probability values close to 50% (essentially a coin toss as to whether success on the variable equates to winning or losing). From a practical perspective, this level of probability would not suggest that the variable was important although variables cannot be considered in isolation (which regression results tends to suggest). Sports performance can be broken down into its constituent parts but these parts need to be considered in relation to other variables, although which ones and how are not clear at this stage.

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 regression analyses found completed sets to be a KPI with the decision tree analysis suggesting that when teams were evenly matched on metres gained, the next best variable to increase the chance of success was to match or outperform the opponents on completed sets. Most interpretations of significant variables tend to focus on the team being analysed e.g. a completed set is a successful run of possessions meaning that the team in possession has not lost the ball during the set of 5 plays. This is of course an "outcome" and doesn't inform on the processes undertaken successfully to enable this 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 is important as these are the things that can be practised and improved. For this reason, it is sensible to suggest that for a performance analysis to be useful, information relating to the processes that determine successful performance, must be provided. This suggest that the stepwise regression approach is not the best approach for eliciting the key aspects of performance from a coaching perspective, as critical process variables are left out of the final model.

The machine learning decision trees provided a very simple and interpretable explanation of the complex data set determining that teams won 97.5% of the time when outperforming opponents by at least 260 metres. For matches where large differences in metres gained were not apparent, differences in completed sets and first carry metres were often apparent in winning performances. Unfortunately, these findings simply reiterate what was apparent in the regression analyses, in that winning is predominately associated with superiority in achieving the main outcome of performance, namely gaining metres. Completed sets can be considered a proxy of gaining metres since the two are intrinsically linked, you can’t gain metres without maintaining possession and if you are successful at maintaining possession you successfully completes sets. This analysis succinctly makes this point but again doesn’t inform the coaching process apart from confirming that there are no individual process variables which are strongly associated with success. This finding may be a consequence of analysing multiple teams together as teams are highly likely to play with different tactical approaches. 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.

3.5 CONCLUSION

An objective method for identifying and categorising PIs and KPIs 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 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.

CHAPTER 4: USING PRINCIPAL COMPONENT ANALYSIS TO IDENTIFY PERFORMANCE INDICATORS & SCORE TEAM PERFORMANCES IN PROFESSIONAL RUGBY LEAGUE

4.1 INTRODUCTION

Rugby league papers typically focus on fatigue (Waldron, Thomson and Twist, 2017) and anthropometric and physical qualities of players (Till et al, 2017). Few papers have identified variables that relate to success known as performance indicators (Cupples and O'Connor, 2011; Woods, Sinclair & Robertson, 2017). Woods et al. (2017) analysed 376 team observations taken from a publicly available statistics website, using 13 team performance indicators to assess their effect on match outcome and final league position in the 2016 Australian NRL competition 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 does not give meaningful information for readers, as it is simply a proxy for tries. Papers that are investigating performance should exclude variables that directly relate to scoring, so that more meaningful information can be gained. Furthermore, the methods indicate that they analysed team performances in isolation whereas better context could be gained by making the data relative to the opposition (Hughes and Bartlett, 2002). However, the use of decision trees appeared to provide more informative results in regard to how performances on variables can lead to winning or losing depending on the frequency performed. This allows for an easier interpretation of results for practitioners and coaches in comparison to regression outputs and could be utilised to identify key performance indicators.

Bracewell (2003) created a scoring system for individual players in a New Zealand rugby union competition, advocating the use of dimension reduction techniques due to performance variables typically being highly correlated with each other. One of these techniques, principal component analysis (PCA) can be used to identify how variables are structured and to reduce a large dataset whilst retaining as much information as possible. For example, in rugby league it could help to group together variables that are explaining the same variance e.g. play the ball and completed sets, which is problematic in regression analysis due to multicollinearity. For example, in study one, the backwards regression model removed breaks from the final model despite previous research highlighting its importance (Woods et al., 2017). This issue can be resolved using PCA, although this method has rarely been used in performance analysis research, probably due to the large sample size (approximately 300 cases) required (Field, 2009).

Mackenzie and Cushion (2013) discussed the 'theory to practice gap', suggesting that many papers lack relevance or usefulness to practitioners, recommending that future performance analysis research address this issue. Principal component analysis (PCA) has been argued to be difficult for coaches to interpret (O'Donoghue, 2008), however, analysing variables independently of each other can also be misrepresentative as they can be related to performance on other variables. For example, Woods et al. (2017) found that line breaks could help determine whether a team won or lost a game. However, breaks are dependent on other variables such as carries and possibly metres. Therefore, presenting this variable in isolation is arguably more unrepresentative in terms of real-world impact. Rugby league performance is complex and multi-faceted, success can depend on performances on multiple variables which are dependent/reliant on each other. Therefore, it is suggested that PCA can produce more relevant results, as it can explain that improving a set of correlated variables i.e. carries, metres and line breaks, will lead to a higher component score, and could lead to a better chance of winning. Furthermore, the component scores can be calculated and run in a regression model to identify how well these components can predict success. This can provide coaches and analysts with more informative results to aid training and tactical methods.

When using regression methods, backwards elimination techniques has been recommended for sport performance (Atkinson & Nevill, 2001), which removes variables sequentially based on its contribution to the models' dependent variable i.e. match outcome for PIs. However, this comes at a reduction of predictive ability, albeit generally small, at each step. Actions such as forty-twenty kicks or red cards occur less frequently than other variables and therefore may be excluded when using these stepwise methods. Therefore, PA studies should assess the suitability of stepwise methods when their dataset includes similar low-occurring variables which can be made redundant in regression analysis, but potentially have a big influence on success when they ensue. For example, when using PCA, stepwise methods may not be necessary due to the variables already being reduced to a manageable size. However, authors should investigate this according to their own particular datasets.

Therefore, due to the identified issues when analysing variables in isolation, evidenced through the previous study when using regression, this study will use PCA to reduce the dataset and score performance. Furthermore, this study will identify PIs using regression analysis and assess the suitability of stepwise methods. Further to this, decision trees will be utilised to identify KPIs.

4.2 METHODS

4.2.1 SAMPLE

Refer to section 3.2.1.

4.2.2 ACTION VARIABLES

All variables were made relative by subtracting the away team's performance from the home team's. Hence positive values resulted when the home team outperformed the away and negative for the opposite. Team and opposition quality was assessed using 5 measures of form (Table 3.1) using either points gained or final league positions (Appendix 3.2). Where lower values equated to better performance (all league position variables) the values were reverse scored i.e. away score minus home score, to ensure positive values always equated to success. Variables that related to scoring were excluded from the analysis to provide more informative results.

4.2.3 STATISTICS

Principal component analysis was used to better understand the structure of the variables and to reduce the dataset to a more manageable size to overcome multicollinearity issues in regression using IBM SPSS Statistics package (v21, IBM Corp., New York, USA). To enable a clear comparison of variables between winning and losing teams, draws (n=22) were excluded. The principal component scores saved from the PCA was run in both Linear (Points difference) and Logistic (Win/Loss) regression with backwards stepwise methods and then without, using a data splitting method (Field, 2009, p.222) on a random selection of 75% of the data. The model produced was then used to predict match outcome using the same variables for the remaining 25% data using Minitab (v17, Minitab Inc., State College, PA). Crosstabs were performed to compare the predicted probabilities produced by the model per game to the actual match outcome. Probabilities were re-coded into winning probability (0.5-1) and losing probability (0-0.49).

Standardized residuals were analysed to ensure no bias in the regression models, if cases were within the recommended limits (Field, 2009, p.293). VIF ($\leq$ 2.11) they were not reported as there were no indications of collinearity issues (Field (2009, p.242). Cooks distances were also analysed to ensure all values were <1 (Field, 2009, p.293) and inly reported if this assumption was violated.

An exhaustive CHAID decision tree was grown using win/loss as the binary response variable in IBM SPSS Statistics package (v21, IBM Corp., New York, USA).

4.3 RESULTS

Principal component analysis (PCA) was conducted on 45 action variables (Appendix 4.1) with orthogonal rotation (varimax method) with scores saved using the Anderson-Rubin method. Ten components (Figure 4.1), which explained 73.4% of the variance (Appendix 4.2), were retained because of the large sample size and for having eigenvalues >1.

The contribution of variables to the principle component scores is shown through the estimated correlations. If the variable had a positive value, it improved the component score. Conversely, when the variable had a negative value, for example missed tackles, the component score for making quick ground reduced.

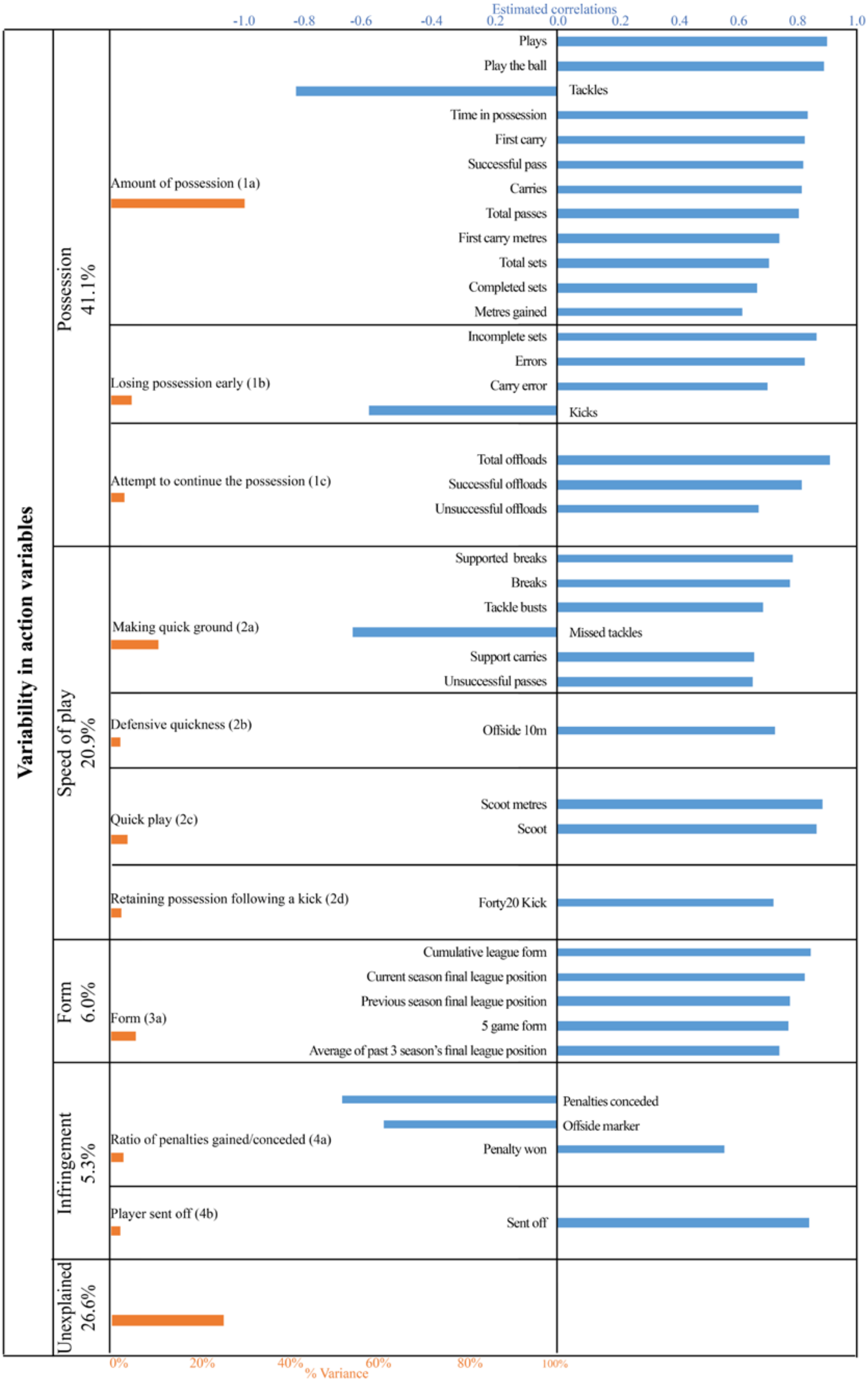


Figure 4.1. Infographic chart displaying the ten principal components, estimated correlations (EC) for variable loadings (ECs between -0.59 and 0.59 were excluded) and the variance in the dataset that each component explained (orange bars).

4.3.1 MODEL 1 – BACKWARD LOGISTIC REGRESSION

Backward logistic regression (Table 4.1) removed the least important components (n = 5) sequentially based on the likelihood-ratio for each variable (Field 2009, p.272). Five variables were retained in the model which suggested that if a team increased the ‘amount of possession’ variable by one unit (principle components are standardised scores which means that a one-unit increase is equivalent to an increase in performance on that variable from say 0 to 1 i.e. the 50th percentile to the 84th percentile) would improve their chance of winning by 90.2% (OR=9.2) from what it was without this increase.

Table 4.1. Model 1 – Backwards logistic regression using the PCA scores to predict win/loss

Variables	β (SE)	OR	95% CI		Probability
			LB	UB	
(Constant)	1.0 (0.2)***				
Making quick ground (2a)	2.5 (0.3)***	12.7	7.0	22.8	92.7%
Amount of possession (1a)	2.2 (0.3)***	9.2	5.4	15.8	90.2%
Form (3a)	1.5 (0.2)***	4.6	3.0	7.1	82.1%
Quick play (2c)	1.2 (0.2)***	3.3	2.2	5.0	76.8%
Losing possession early (1b)	-0.9 (0.2)***	0.4	0.3	0.6	20.5%

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

Similarly, if a team increased their performance on the ‘quick play’ score by one unit i.e. they made more scoots and scoot metres, they would increase their chances of winning by 76.8% (OR=3.3). However, the 95% confidence intervals for the odds ratio for quick plays (2.2 - 5.0) demonstrate the degree of uncertainty of this prediction.

4.3.2 MODEL 2 – FORCED ENTRY LOGISTIC REGRESSION

The ten principal components were run in a Logistic regression without stepwise methods (Table 4.2). 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)

Table 4.2. Model 2 - Principal components that best predicted match outcome in rugby league

Variables	β (SE)	OR	95% CI		Probability
			LB	UB	
(Constant)	1.0 (0.2)***	0.2			
Making quick ground (2a)	2.6 (0.3)***	13.3	7.3	24.4	93.0%
Amount of possession (1a)	2.3 (0.3)***	10.1	5.7	18.0	91.0%
Form (3a)	1.5 (0.2)***	4.7	3.0	7.3	82.4%
Quick play (2c)	1.2 (0.2)***	3.4	2.3	5.1	77.5%
Ratio of penalties gained/conceded (4a)	0.2 (0.2)	1.3	0.9	1.8	55.7%
Defensive quickness (2b)	0.2 (0.2)	1.2	0.9	1.7	54.9%
Player sent off (4b)	-0.1 (0.1)	0.9	0.7	1.3	47.2%
Retaining possession following a kick (2d)	-0.2 (0.2)	0.8	0.6	1.1	40.3%
Attempt to continue the possession (1c)	-0.3 (0.2)	0.8	0.5	1.1	38.8%
Losing possession early (1b)	-0.9 (0.2)***	0.4	0.3	0.6	20.6%

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

4.3.3 CROSS-VALIDATION OF MODEL 1 AND 2

The two regression models (based on 75% of the data) were run on the remaining 25% of the data with similarly accurate predictions of the probability of winning (Table 4.3).

Table 4.3. The predicted probabilities vs match outcome

Dataset	Match outcome	Predicted Loss		Predicted Win	
		N	%	N	%
Backward LR 75%	Win	26	10.5%	221	89.5%
	Loss	140	84.3%	26	15.7%
Backward LR 25%	Win	7	9.5%	67	90.5%
	Loss	50	86.2%	8	13.8%
LR 75%	Win	29	11.7%	218	88.3%
	Loss	139	83.7%	27	16.3%
LR 25%	Win	7	9.5%	67	90.5%
	Loss	50	86.2%	8	13.8%

4.3.4 MODEL 3 – BACKWARD LINEAR REGRESSION

Backwards linear regression (Table 4.4) removed the least important components (attempt to continue the possession, ratio of penalties gained/conceded, retain possession following a kick & player sent off) sequentially based on the significance value of the t-test statistic (Field 2009, p.213).

81.6% of the variance in points difference was accounted for in the final model which included 6 principal components and predicted that increasing the ‘making quick ground’ principle component (standardised variable) by one unit would add on average 15.6 points (14.6 - 16.6) to their final score.

Table 4.4. Model 3 - Reduced set of principal components that best predicted points difference in rugby league

Variables	β (SE)	95%CI	
		LB	UB
(Constant)	5.1 (0.5)***	4.1	6.1
Making quick ground (2a)	15.6 (0.5)***	14.6	16.6
Amount of possession (1a)	12.0 (0.5)***	11.0	13.0
Form (3a)	7.9 (0.5)***	6.9	8.9
Quick play (2c)	5.1 (0.5)***	4.1	6.1
Defensive quickness (2b)	1.9 (0.5)***	0.9	2.9
Losing possession early (1b)	-2.6 (0.5)***	-3.6	-1.6

Key: β is the unstandardized beta coefficient, SE is the standard error, 95% CI is the 95% confidence intervals, LB is lower boundary of CI and UB is upper boundary of CI, *p<.05, **p<.01, ***p<.001.

4.3.4.1 RESIDUAL ANALYSIS

One outlier was identified in the residual analysis (>3, Table 4.5). The regression model correctly identified the result as a home win, albeit by 11 points as opposed to the actual 44 points. In this match, two variables (amount of possession and quick plays) had values which were negative and counter to what was expected by the model. However, the remaining four variables were consistent with the rest of the data and hence the model predicted the correct result.

Table 4.5. Principal component scores and model predicted values for an outlier identified in residual analysis

Case 245	Predicted	Outlier
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 (-)

4.3.5 MODEL 4 – FORCED ENTRY LINEAR REGRESSION

The ten principal components were entered into a linear regression without stepwise methods (Table 4.6) which explained 81.8% of the variance in point's difference. Of the 4 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 points gained marginally.

Table 4.6. Model 4 - Principal components that best predict points difference in rugby league

Variables	β (SE)	95% CI	
		LB	**UB**
(Constant)	5.1 (0.5)***	4.1	6.1
Making quick ground (2a)	15.6 (0.5)***	14.6	16.6
Amount of possession (1a)	12.0 (0.5)***	11.0	13.0
Form (3a)	7.8 (0.5)***	6.8	8.8
Quick play (2c)	5.1 (0.5)***	4.1	6.1
Defensive quickness (2b)	0.7 (0.5)	0.9	2.9
Player sent off (4b)	-0.1 (0.5)	-0.3	1.7
Retaining possession following a kick (2d)	-0.3 (0.5)	-1.2	0.9
Attempt to continue the possession (1c)	-0.3 (0.5)	-1.3	0.6
Losing possession early (1b)	-2.6 (0.5)***	-1.4	0.7

Note: β is the unstandardized beta coefficient, SE is the standard error, 95% CI is the 95% confidence intervals, LB is lower boundary of CI and UB is upper boundary of CI, *p<.05, **p<.01, ***p<.001

4.3.6 CROSS-VALIDATION OF MODEL 3 AND 4

The model equation was run on the remaining 25% of the data for both models to see how accurately the model equation from the randomly selected 75% of the dataset, could predict the final points difference (Table 4.7). Correlation coefficients were utilised to assess models predicted points difference and actual points difference for both the non-stepwise and the backwards regression models.

Table 4.7 – Correlation coefficients of predicted points difference with observed points difference

Dataset (predicted points difference)	r
Backward LR 75%	0.904***
Backward LR 25%	0.906***
LR 75%	0.904***
LR 25%	0.908***

4.3.7 EXHAUSTIVE CHAID DECISION TREE (MACHINE LEARNING)

A machine learning (data mining) technique was used to create a decision tree model to predict winning and losing (Figure 4.2) from a training sample of 75%, and cross-validated against a test sample of 25% of the data. The decision tree showed the most important principal components being making quick ground, followed by amount of possession and finally form.

The training sample (Appendix 4.3) was able to correctly classify 76.0% of games and the cross-validation revealed that it could classify 78.8% of games correctly from the test sample (Table 4.8).

Table 4.8 Classification Table for the training (75%) and test (25%) samples.

Sample	Observed	Predicted		Percent Correct	Overall % correct
		Loss	Win		
Training	Loss	128	38	77.1%	76.0%
	Win	61	186	75.3%	
Test	Loss	51	7	87.9%	78.8%
	Win	21	53	71.6%	

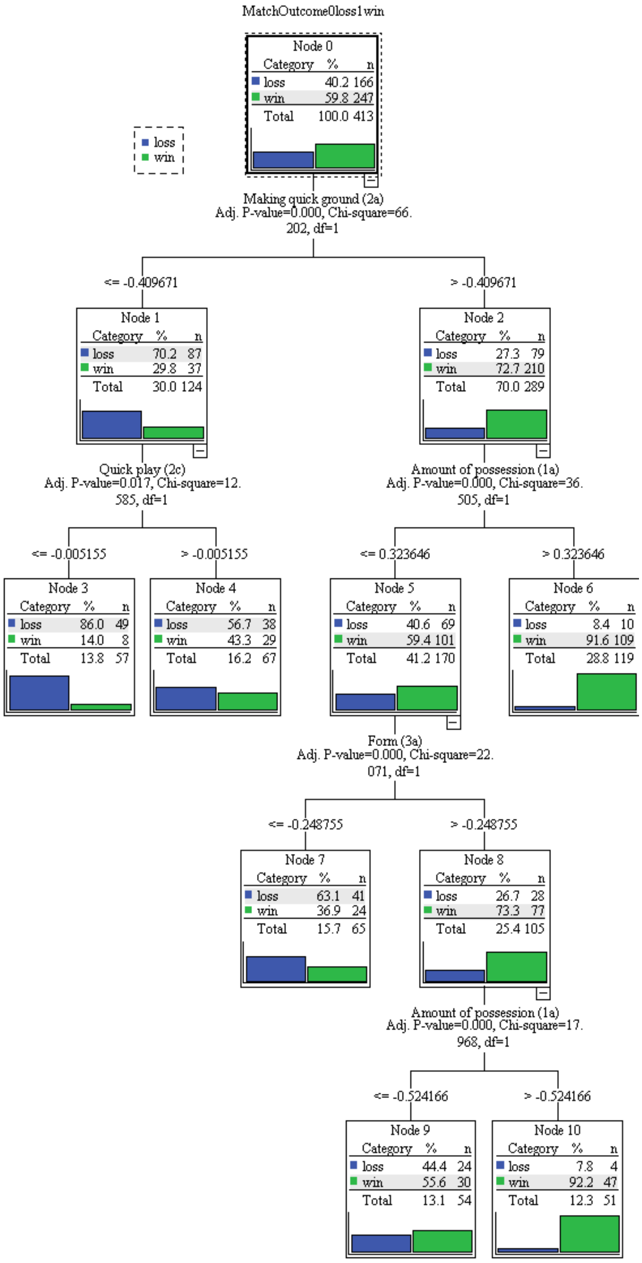


Figure 4.2. Exhaustive CHAID interaction trees on the training sample (75%)

4.3.8 SUMMARY OF THE FOUR REGRESSION MODELS

Key performance indicators were defined as variables that remained in the final decision tree and performance indicators were defined as components that remained in the final logistic regression model (Table 4.9).

Table 4.9. Summary of PCA PIs and KPIs

Variables	EV	Logistic Backwards			Logistic Enter			Linear Backwards			Linear Enter			In final decision tree	PI/ KPI
		OR	95% CI LB	95% CI UB	OR	95% CI LB	95% CI UB	β	95% CI LB	95% CI UB	β	95% CI LB	95% CI UB		
Amount of possession (1a)	14.7	9.2	5.4	15.8	10.1	5.7	18.0	12.0	11.0	13.0	12.0	11.0	13.0	Yes	KPI
Making quick ground (2a)	5.2	12.7	7.0	22.8	13.3	7.3	24.4	15.6	14.6	16.6	15.6	14.6	16.6	Yes	KPI
Form (3a)	2.7	4.6	3.0	7.1	4.7	3.0	7.3	7.9	6.9	8.9	7.8	6.8	8.8	Yes	KPI
Losing possession early (1b)	2.3	0.4	0.3	0.6	0.4	0.3	0.6	-2.6	-3.6	-1.6	-2.6	-3.5	-1.6		PI
Quick play (2c)	1.9	3.3	2.2	4.9	3.4	2.3	5.1	5.1	4.1	6.1	5.1	4.1	6.1		PI
Attempt to continue the possession (1c)	1.5				0.8	0.5	1.1				-0.3	-1.4	0.7		
Ratio of penalties gained/conceded (4a)	1.4				1.3	0.9	1.8				0.7	-0.3	1.7		
Retaining possession following a kick (2d)	1.2				0.8	0.6	1.1				-0.1	-1.2	0.9		
Defensive quickness (2b)	1.1				1.2	0.9	1.7	1.9	0.9	2.9	1.9	0.9	2.9		PI
Player sent off (4b)	1.0				0.9	0.7	1.3				-0.3	-1.3	0.6		

Note: EV is the Eigenvalue, OR is Odds ratio, 95% CI is 95% confidence intervals, LB is lower boundary of CI and UB is upper boundary of CI, β is the unstandardized beta coefficient. PI identified from backwards regression models, KPIs identified from decision trees.

4.4 DISCUSSION

The identification of variables that lead to success is an integral part of performance analysis. Coaches and athletes are constantly trying to understand how to improve performance, performance analysis aids this process particularly through the identification of reliable PIs and KPIs. This investigation aimed to a) reduce the dataset whilst retaining as much of the variance as possible, using principal component analysis, b) assess the suitability of the principal components in predicting match outcome (logistic regression and decision trees) and final points difference (linear regression), c) provide results that are relevant and transferable for practitioners.

The principal component analysis created ten principal components, which were grouped into four main categories, explaining 73.4% of the dataset. These were possession (41.1%), speed of play (20.9%), form (6.0%) and infringements (5.3%), with 26.4% of the variance not explained. The separation of possession and speed of play was an important distinction previously not seen (study 1), however it is important as rugby league is a territorial game, with teams having to score by moving the ball past their opponent's try line. Therefore, teams that can speed up their plays are thought to gain more metres as the defending team have less time to organise their defensive line adequately. The variable 'retaining possession following a kick' loaded onto 'speed of play' possibly because teams that were successful on the other speed variables were more successful at retaining possession following restarts, logically speed would play a part in this. Success on this variable can give a significant territorial advantage to a team and can easily be coached in terms of strategies to maximise the potential for retaining possession. Similarly, defensive quickness can 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, as was previously concluded in study 1. 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, highlighted in the previous study as important, which enabled the analysis to consider the differential in team qualities. In previous regression analyses (study 1) form was inconsistently associated with match outcome whereas in this study its effect was consistent, albeit small (6%). However, as identified in study 1, 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 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 positively loaded variable; 10m offside, where teams were caught offside at the 10m mark following a tackle, more times than the opponents. An explanation could be that whilst defending, the team could have a strategy of sending more players in to the tackle to dominate the attacking player and prevent a quick play the ball, therefore delaying the defensive retreat to the referee. On the other hand, it could be due to the team having a strategy of 'line speed' where the defending team attempt to leave the line quickly to prevent the opposition from gaining metres, and in the process receiving a penalty against them for leaving the defensive line prior to the ball being played by the opponents.

The pairwise measures of association revealed a trivial reduction in predictive ability when stepwise methods were utilised. This reduction of components provided an easier 'take-away message' for practitioners, however the principal components that were removed could be the difference between winning and losing in closely contested matches, and therefore performances on these excluded components may give teams the competitive edge to win. Butterworth, O'Donoghue and Cropley (2013) mentioned the potential importance of minute 'performance gains' to winning and losing on occasions in sport in their review of performance profiling literature, however this approach gained significant media attention after GB Cycling attributed their 7 gold medals in the 2012 London Olympics to their 'marginal gains' philosophy (Slater, 2012). This is where they aimed to improve every component of cycling by 1%, with the collective improvements resulting in better performance overall. As such, this study agreed with the findings from the previous chapter, in that it would seem stepwise procedures are not sensible for analysing complex sports as variables with relatively low explanatory powers are removed whereas it is reasonable to believe that these could make a significant difference to a match outcome, particularly in closely contested matches. Sport is a dynamic and multi-faceted process where performance depends on the interaction, usually reactive to the opposition, in both team and individual sports.

Decision trees were utilised to identify key performance indicators, which could be interpreted with ease by practitioners. Despite the transferability of results, the cross-validation revealed that their predictive ability was slightly lower than the regression methods. The component that explained the most amount of variance in the dataset was amount of possession, which described that improving the team's ability to retain possession of the ball is critical to increasing the probability of winning, which can be achieved by improving the associated variables. However, the decision trees indicated that making quick ground was the most important variable that could increase the home team's chances of winning to 72.7%, increasing to 91.6% when also increasing the amount of possession. However, large differences were evident in the confidence intervals (lower 7.0 and upper 22.8) for making quick ground, this could be attributed to the large variation between team qualities in the dataset. For example, top rated teams would be expected to make quick ground more than lower rated teams. Furthermore, each team would be expected to perform differently to each other as shown through the differences in confidence intervals. Therefore, future studies could consider creating nomothetic performance profiles to understand how performances on principal components generally differ according to team quality and idiographic profiles for a more informative understanding of individual team performances on principal components.

The previous chapter identified numerous issues with regression models when using variables that were correlated with each other. This was evidenced through the peculiar results when two form variables were retained in the final model, with opposing effects. Therefore, it was suggested that principal component analysis could overcome this issue by grouping together correlated variables into an orthogonal principal factor. In this study, all the form variables positively loaded onto one principal component (Form 3a), suggesting that the use of PCA was appropriate as it seemingly solved the issue of multicollinearity and some inexplicable results from study 1. In addition, this study found that cumulative league form loaded the highest onto the form principal component, followed by final league position. This suggested that Carling, Wright, Nelson and Bradley's (2014) comments, which recommended the use of current form as a more appropriate and fairer method to assess team quality, were justified. Future research into other sports should consider using this measure of team quality, and assess its suitability according to the sport analysed.

The previous chapter identified several cases in the residual analysis where the model was unable to accurately predict as performances on certain variables were unexpected. The use of principal component analysis was suggested to be a better approach to analyse performance especially when utilising regression methods which suffer from multicollinearity issues, by forming orthogonal components comprised of related variables. The suitability of this decision was evident in the residual analysis as only one outlier was identified from the large sample size. This outlier highlighted that although the team had performed on 5 components as expected, two components were unexpected (amount of possession and quick play) which led the model to predict a win by 11 points, which actually resulted in a winning difference of 44 points. This case highlighted the fact that whilst sporting events can follow predictable patterns to some extent e.g. winning teams almost always gain more metres than their opponents and score more tries, large wins, as in this instance, can display unusual patterns in the data, probably due to unusual tactics which could be down to players sent off, player injuries (from either side) or poor playing conditions etc.

Future research should consider the inclusion of cumulative league form when assessing team quality, where appropriate. In addition, performances on KPIs and PIs should be assessed using performance profiling techniques to identify differences between teams. Furthermore, including the effects of independent variables when creating performance profiles is warranted, as this approach can help to provide informative results for practitioners as this study identified large variations on some odds ratio confidence limits.

4.5 CONCLUSION

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

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CHAPTER 5: PRESENTING TEAM PERFORMANCES IN PROFESSIONAL RUGBY LEAGUE USING STANDARDISED PRINCIPLE COMPONENT SCORES ACCORDING TO TEAM QUALITY, MATCH VENUE AND MATCH CLOSENESS

5.1 INTRODUCTION

Graphical formats are more often used to represent sports performance in the applied setting as numerical methods are often considered unimaginative and unclear. This can include performance profiles which display team or individual performances on selected action variables and performance indicators. For example, radar graphs (O'Donoghue, 2005) and form charts (Jones, James and Mellalieu, 2008) have been used to represent average performances (see also Hughes, Evans and Wells, 2001; Liu, Yi, Gimenez, Gomez & Lago-Penas, 2015; O'Donoghue, 2005). The two main methods for creating profiles have been medians and their respective confidence intervals (James, Mellalieu & Jones, 2005) and percentiles (O'Donoghue, 2005) although very little development has occurred since (Vinson & Peters, 2016; Liu, Gomez, Goncalves & Sampaio, 2016). There has also been a lack of transparency in terms of how performance indicators have been selected (Eugster, 2012; O'Donoghue, 2005), with the exception of coach-led approaches (James, Mellalieu & Jones, 2005; Taylor, Mellalieu and James, 2004; Vinson and Peters, 2016) or identified from previous research in the same sport but from different competitions (Liu, Gomez, Goncalves & Sampaio, 2016; Liu, Yi, Gimenez, Gomez & Penas, 2015). For performance profiles to be meaningful it could be argued that they should be based on objective and robust performance indicators, which have been identified from the same competition that the profiles are being created for, to ensure that the PIs (and ensuing profiles) are representative of the data they are explaining.

Hughes, Evans and Wells (2001) analysed previous performance profiling papers in order to establish the minimum number of matches that need to be analysed for an average value of a performance indicator (PI) to stabilise. The authors developed a controversial method which attempted to determine how many matches were needed in order to create a stable average for a PI, this involved analysing the evolving mean as additional games were added to the sample. In addition to this, tolerable percentages of the mean were calculated as the evolving mean stabilised, for example 15%, 10% or <5%. Therefore, the number of matches needed for stable profiles can be calculated per performance indicator and ensuing profiles can be deemed to be representative of their typical performance. However, as identified in previous chapters, as the sample size increases, differences in performances can be lost. This point was echoed by O’Donoghue (2005) who also suggested that meaningful differences could be lost and deemed as tolerable with this particular method. In addition, O’Donoghue (2005) points out that the word normative is used in the title of the article perhaps misleadingly as no normative methodologies were evident in the paper. This brings to light the presumption that ‘stable’ profiles can be achieved, however the previous chapters in this thesis have identified that sport, and in particular rugby league, is multi-faceted and dynamic, with 13 players on each side all with different roles and abilities. Therefore, it could be argued that it is not reasonable to expect performances to stabilise and retain vital information which would inevitably be lost when increasing the sample size, as each contest will bring with it a unique set of challenges and performances, especially when taking into account independent variables such as match venue, pitch sizes, referee decisions etc.

Therefore, it would be sensible to agree with James, Mellalieu and Jones (2005) who suggested that stability of profiles may never be achieved due to unpredictability of performances, which is especially prevalent when the particular sport analysed involves interaction with an opponent.

Performance profiling research has been limited in rugby league with performance indicator research (Cupples & O'Connor, 2011; Woods, Sinclair & Robertson, 2017) not extended to create performance profiles. On this basis the profiling undertaken in other sports, professional rugby union (James, Mellalieu & Jones, 2005), soccer (Liu, Gomez Gonvalces & Sampaio, 2016; Liu, Yi, Gimenez, Gomez & Penas, 2015; Taylor, Mellalieu & James, 2004), tennis (O'Donoghue, 2005), hockey (Vinson & Peters, 2016), basketball (Eugster, 2012) and badminton and squash (Hughes, Evans & Wells, 2001) needs to be considered.

Liu, Yi, Gimenez, Gomez and Penas (2015) used performance profiles to illustrate how top, middle and bottom Champions League soccer teams performed on selected action variables identified from previous research. Variables were grouped as; related to scoring, attacking & passing and defending. To add context, three independent variables, opposition quality, match outcome and match venue, were used with separate graphs for each. Radar graphs were presented for each team quality (high, intermediate & low) on a single figure. However, fair comparisons were difficult due to different scales used for each graph. Future studies should use the same scale for each graph if comparisons between them are likely.

James, Mellalieu and Hollely (2002) recommended idiographic assessments of teams to provide meaningful profiles. This is because teams are likely to perform quite differently to each other, due to varying skills of players and differing coaching philosophies, which combine to create unique patterns of play for each team.

Considering this, this study will utilise an idiographic approach to explore the extent to which teams vary in performance, at a much more detailed level than possible with nomothetic approaches. For example, previous chapters (e.g. Tables 3.6 and 4.9) identified relatively large differences in confidence intervals, due to differences between matches, but between (team quality) and within (match venue, opposition quality and match closeness) team differences were not possible to be identified.

Match closeness (final points difference) has been used as an independent variable to differentiate between team performances in rugby union (Vaz, Mouchet, Carreras and Morente, 2011; Vaz, Van Rooyen & Sampaio, 2010). Both studies categorised games as being close (0 to 15 points for IRB games, 0 to 11 points for Super rugby games), balanced (16 to 34 points for IRB games, 12 to 25 points for Super rugby games) and unbalanced games (35 to 53 points for IRB games, 26 to 43 points for Super rugby games). The justification for the points boundaries was relatively arbitrary, albeit logical, with the number of scores required by the losing team (tries can be worth 7 points) determining them. Similarly, Liu, Yi, Gimenez, Gomez and Penas (2015) used two categories for match closeness in soccer, unbalanced (>2 goal difference) and balanced (≤ 2 goal difference), with unbalanced matches removed from the analysis. Whilst this acknowledges the possibility that performances differ significantly between balanced and unbalanced matches the methodology prevented a direct comparison. An alternative approach would be to consider performance from the perspective of a team's match outcome, in this scenario match closeness could, for example, be categorised as unbalanced wins, unbalanced losses and balanced games. This would enable three performance levels to be compared at an individual team level.

Venue has often been shown to play a role in whether teams win or lose matches e.g. in soccer (Garcia-Rubio, Gomez, Lago-Penas & Ibanez, 2015; Mackenzie & Cushion, 2013) and volleyball (Alexandros, Panagiotis & Miltiades, 2012). Despite this, few performance profiling papers (e.g. Liu, Gomez, Goncalves and Sampaio, 2016; Liu, Yi, Gimenez, Gomez and Lago-Penas, 2015) have assessed the impact of venue empirically. Tucker, Mellalieu, James and Taylor (2005) investigated home advantage by analysing 30 matches of an English professional soccer team. Some evidence of home advantage was found, their home win percentage ranged from 56.3% to 59.2%, but there was little variation on most action variables when playing home or away. Since match venue has been shown to effect the outcome of matches but the evidence is less certain for action variables, it would seem sensible to use this as an independent variable when producing profiles for rugby league teams.

Principal component analysis (PCA) is used to reduce a large dataset into structured clusters to represent a number of highly correlated variables with minimal loss of predictive ability. This method was used in the previous chapter to identify how performing well (standard score >1), indifferently (between -1 and +1), or badly (<-1), relative to the opponent on a principal component i.e. a set of related action variables, impacts on the performance outcome.

Coaches and performance analysts overall aim is to try to improve sporting performance, this can be achieved through 'performance modelling" which is predicting future performances based on previous performance (James, 2012; James, Mellalieu & Jones, 2005). This information can aid the coaching process by providing valuable information on their own team's predicted performance as well as the opposition's, aiding the identification of strengths and weaknesses. Recent performances would be expected to be more important than older performances, therefore some form of smoothing algorithm that weights more recent performances higher than older ones could aid prediction accuracy.

This chapter will use the principal component scores derived in the previous chapter (see Figure 4.1), to create nomothetic profiles according to team quality and idiographic profiles for selected teams whilst accounting for match closeness and venue.

5.2 METHODS

5.2.1 SAMPLE

Refer to section 3.2.1.

5.2.2 STANDARDISED PCA SCORES

Standardised PCA scores for the ten principal components identified in the previous study (see Figure 4.1), were saved using the Anderson-Rubin method to ensure orthogonality. Team performances on these scores were assessed according to team quality - determined by the average finishing position over the three seasons (Appendix 3.2), match venue and match closeness - classified by match outcome as balanced (points difference -12 to 12) or unbalanced (win >12 or loss >12).

5.2.3 TABLES WITH CONDITIONAL FORMATTING

Three top, middle and bottom quality teams' performances on the principal components were visually compared using Tables with conditional formatting (CF, for an example see Appendix 5.2). CF provides a clear visual discrimination of performances, in this instance using different colours for each cell i.e. dark red (values < -1), light red (between -1 & 0), yellow (between 0 & 1) and green (>1).

5.2.4 PERFORMANCE PROFILES

Forest plots were created to compare team performances on principal components according to team quality and match venue using means and standard deviations. These measures were selected due to the large data samples, with normal distributions, to display the variation in the data. Radar graphs were then created to display a top, middle and bottom rated team's performances according to match closeness and match venue using medians and 95% confidence intervals. Due to the small samples and the more varied nature of the distributions, normality was less evident (Appendix 5.3 & 5.4), a depiction of the likelihood (confidence interval) of typical performance (median) was selected.

For variables where lower values equated to success the sign of the score was reversed (as in Chapter 4). This meant that positive values **always** signified better performance which aids interpretation and minimises the chance of confusion.

5.2.5 CASE-STUDY

A match contested by two top rated teams (St Helens versus Warrington, referred to as the upcoming match) was randomly selected for analysis from all such matches where both teams had played at least 6 prior matches at home (for the home team) or away (for the away team) against top rated teams. These preceding 6 matches for each team were analysed as if undertaken prior to the upcoming match. Radar charts presented a summary of the six matches (medians and their 95% confidence intervals). Form charts presented a breakdown of each match on each principal component score.

An exponential smoothing algorithm was used to predict principal component scores for the upcoming match. The algorithm used all previous matches in the data set for St Helens playing at home against top teams (n=10) and Warrington playing away (n=7). A team's recent performances on each principal component score (previous match scores) might have been relatively stable over time, fluctuated significantly, been improving etc. Exponential smoothing can weight newer performances more than older ones (using a low smoothing constant) or average all previous scores similarly (high smoothing constant). To determine the value of the smoothing constant (between 0 and 1) values between 0.1 and 0.9 were tested for all principal components for both teams (Appendix 5.5 & 5.6) and the one resulting in the lowest root mean square error selected to calculate each algorithm (Table 5.1 & Appendices 5.7 to 5. 25).

Smoothing algorithms need to be initialised i.e. a starting value which can be calculated from previous data such as an average. Given that the previous season's data was subject to different team personnel, different coach etc. the initial predicted score for Match 2 (Table 5.1) was set as the principal component score value from Match 1. Match 3's predicted score was then calculated using a 0.1 weighting (lowest root mean square error value in Appendix 5.5) using the formula:

$$(P_{match3} = 0.1 * F_{match2} + (1 - 0.1) * P_{match2})$$

Table 5.1 Exponential smoothing for Amount of possession component - St Helens

	Amount of possession (F)	Predicted Score (P)	Error	Absolute error	Square error
Match 1	-0.86				
Match 2	-0.19	-0.86	0.67	0.67	0.45
Match 3	1.51	-0.80	2.31	2.31	5.33
Match 4	-0.76	-0.57	-0.19	0.19	0.04
Match 5	-0.87	-0.59	-0.28	0.28	0.08
Match 6	-0.80	-0.61	-0.19	0.19	0.04
Match 7	0.15	-0.63	0.78	0.78	0.61
Match 8	-0.14	-0.55	0.41	0.41	0.17
Match 9	-1.08	-0.51	-0.57	0.57	0.32
Match 10	0.54	-0.57	1.11	1.11	1.24
Predicted		**-0.46**			
Average			0.45	0.72	0.92
RMSE					0.96

Note: RMSE is Root mean square error

5.3 RESULTS

5.3.1 TOP, MIDDLE AND BOTTOM TEAMS' PERFORMANCE PROFILES

Principle component profiles suggested that very little difference existed between top, middle and bottom rated teams (Figure 5.1) with the greatest difference in mean values for form, making quick ground and quick plays. Bottom rated teams performed slightly worse on losing possession early compared to the higher rated teams. Middle teams tended to outperform the other teams on attempts to continue possession and the ratio of penalties gained to conceded. Top teams retained more possessions following a kick than bottom and middle teams.

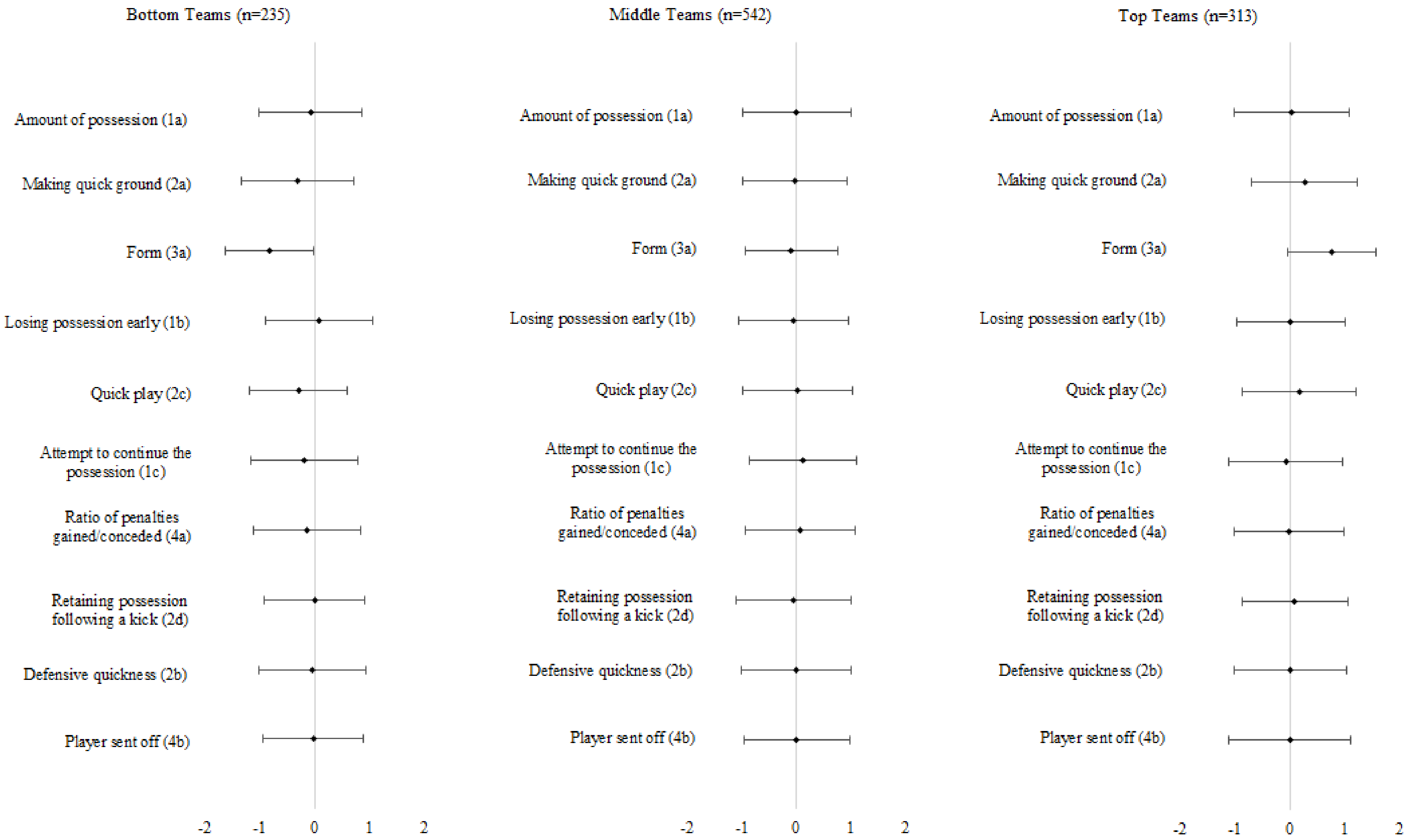

Figure 5.1. Principal component profiles (means and standard deviations) for top, middle and bottom rated teams

5.3.2 INDIVIDUAL TEAMS' PERFORMANCE PROFILES

5.3.2.1 WIGAN'S (TOP TEAM) PERFORMANCE PROFILES

Wigan's profile in unbalanced home wins suggested they tended to perform well (in comparison to league average performance i.e. 0) on the amount of possession, making quick ground, defensive quickness and quick plays. Performance on these variables tended to be lower for both balanced home games and unbalanced home losses. Form, which included cumulative league form, also tended to be slightly lower in line with worse results. In unbalanced away wins, Wigan tended to perform at similar levels to when they had unbalanced wins at home. Similar to their home performance, their profiles in balanced away games dropped off slightly compared to unbalanced away wins but in unbalanced away losses relatively large in performance across matches was evident, particularly for defensive quickness, quick plays, retaining possession following a kick and form.

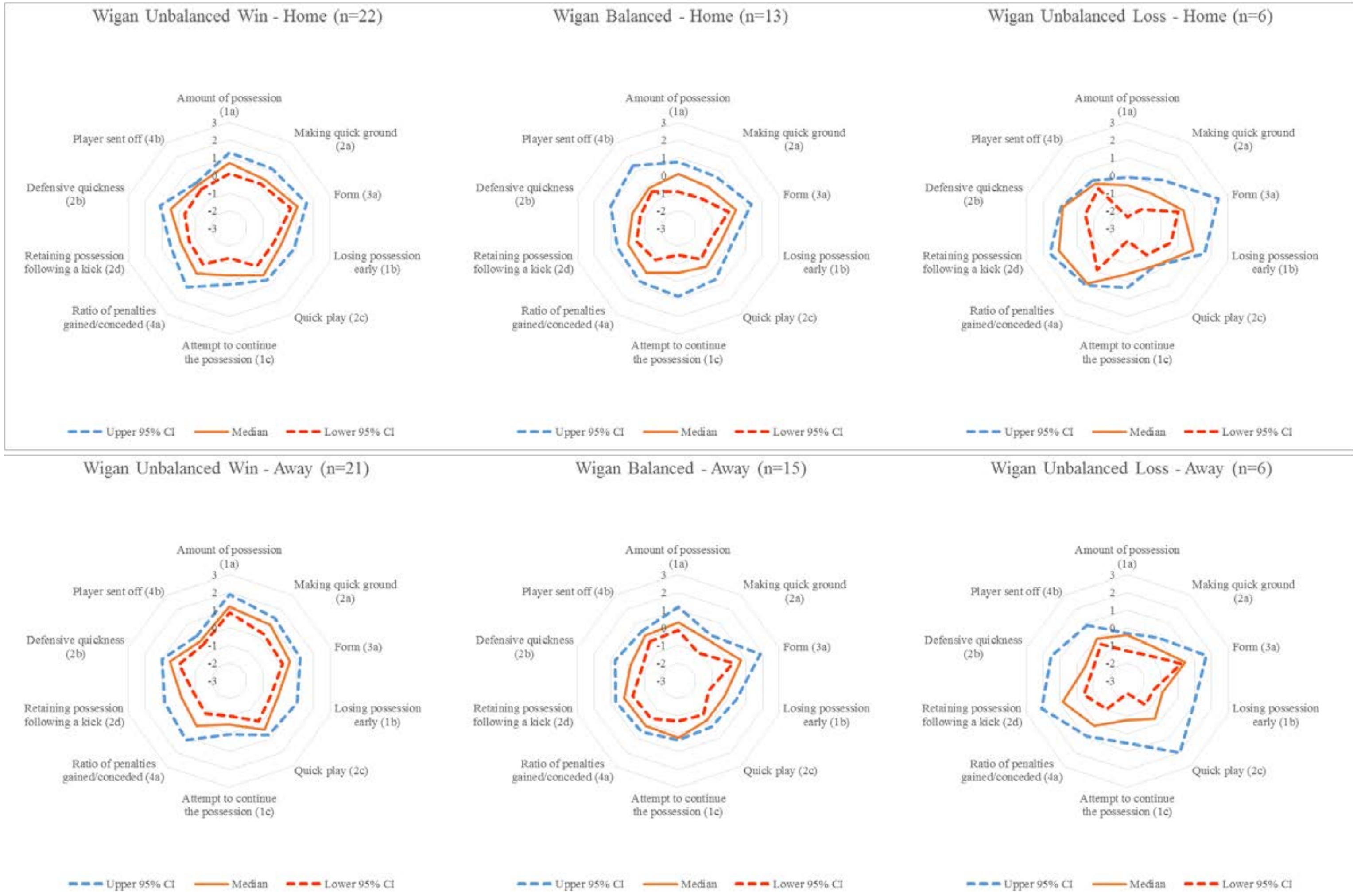

Figure 5.2 Performance profiles for Wigan according to match closeness and match venue

5.3.2.2 HULL FC'S (MIDDLE TEAM) PERFORMANCE PROFILES

In unbalanced home wins Hull FC performed more consistently at their best levels on making quick ground and avoiding losing possession early, were quite variable in their performance on defensive quickness and retaining possession following a kick which were based on typically league average possession (Figure 5.3). In balanced home games Hull FC sometimes had very poor performance on retaining possession following a kick and losing possession early (both lowest 5% of league performance). Quick plays varied considerably from a top 5% to a bottom 1% league performance during unbalanced away wins where their form was consistently better than their average. This variability was also evident in unbalanced away losses where their form was sometimes lower than their average.

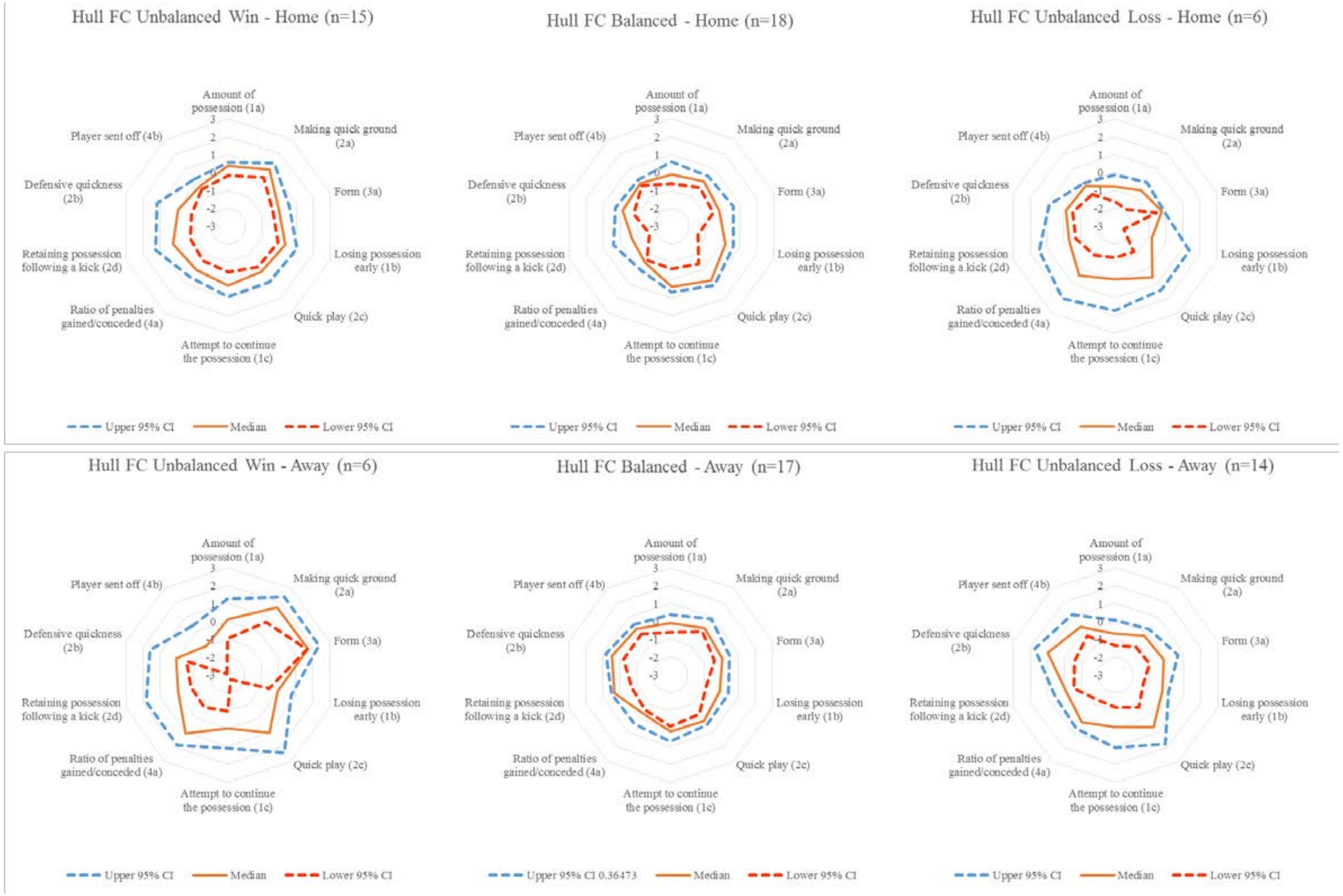

Figure 5.3 Performance profiles for Hull FC according to match closeness and match venue

5.3.2.3 WIDNES (BOTTOM TEAM) PERFORMANCE PROFILES

At home, for both unbalanced wins and balanced matches, Widnes performed around the league average on all principal component scores, with form reflecting their overall low rank. In unbalanced home losses Widnes had more varied scores for attempting to continue possession and losing possession early. In unbalanced away wins, Widnes sometimes had very high amounts of possession (top 1%) along with not losing possession early (top 1%) even though their average performance on these scores were at the league average.

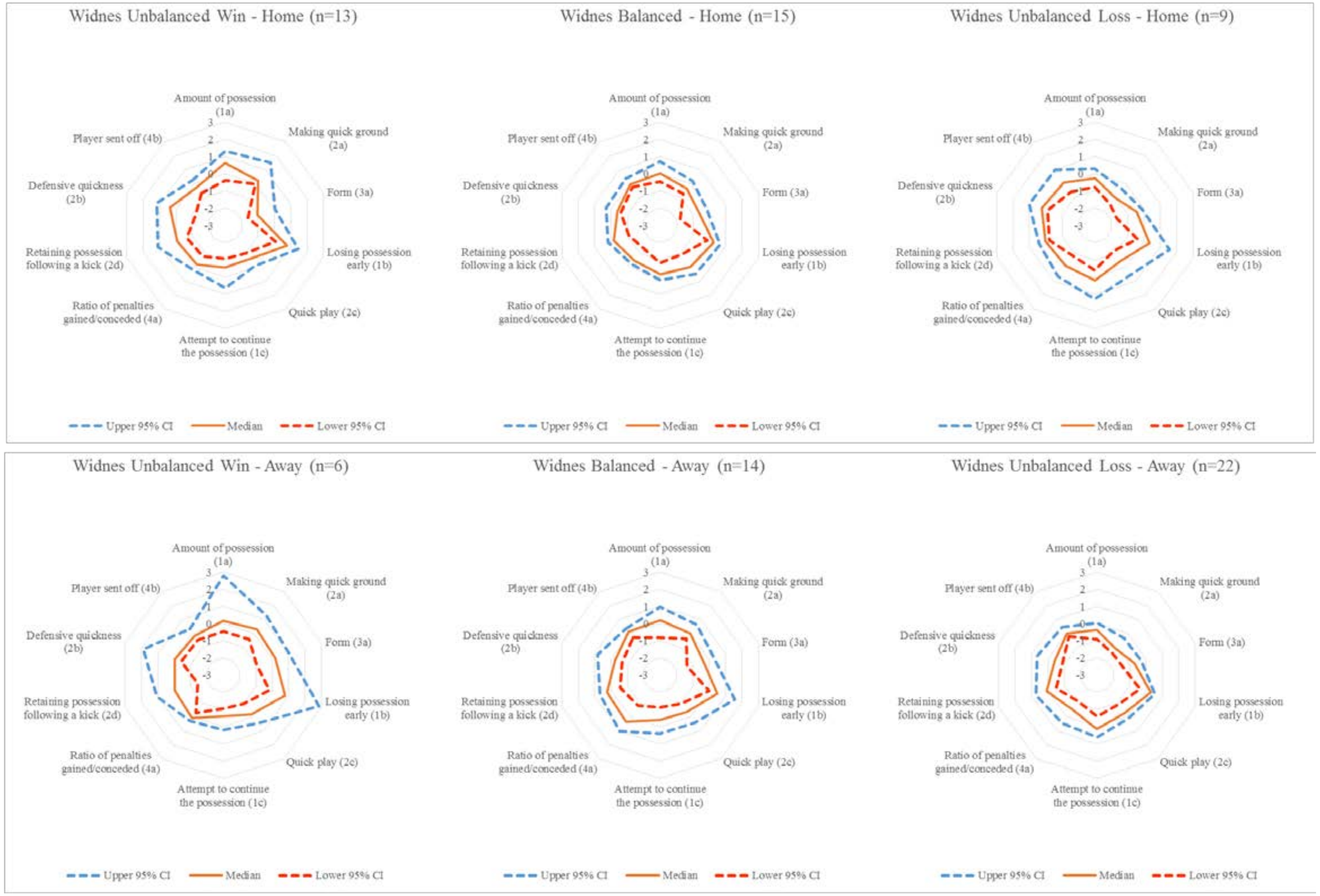

Figure 5.4 Performance profiles for Widnes according to match closeness and match venue

5.3.3 CASE STUDY –ST HELENS VS WARRINGTON

St Helens tended to perform at overall league average on all principal component scores although very low scores were evident for quick plays and making quick ground (Figure 5.5).

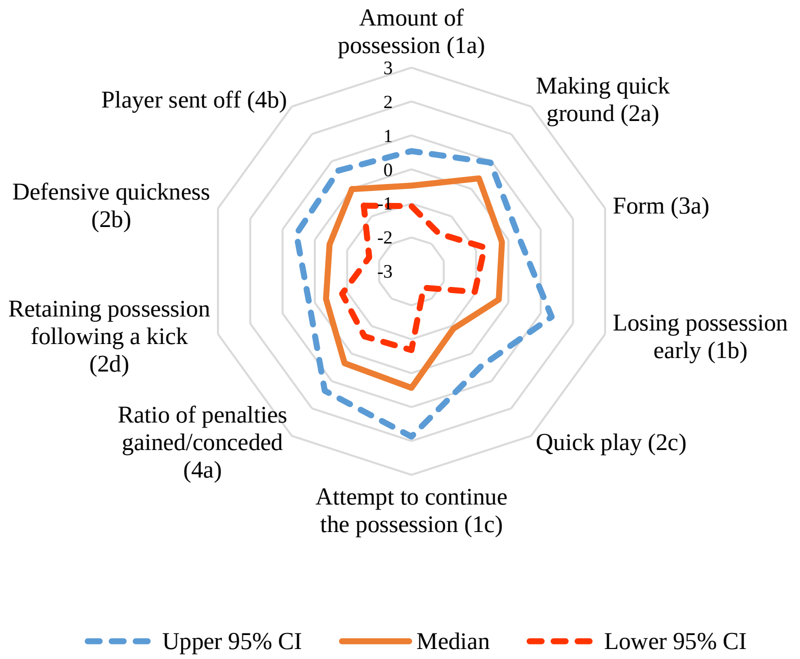

Figure 5.5. St Helens' home performance on principal components scores in 6 preceding matches against top rated teams

A visual depiction of St Helens performances on a match to match basis for their last 6 home games playing against top teams clearly showed a consistent improvement on both making quick ground and ratio of penalties gained/conceded principle component scores (Figure 5.6). However, they performed poorly on amount of possession and retaining possession following kicks. With quick plays standing out as being consistently low (against league standard) performance levels in the most recent matches.

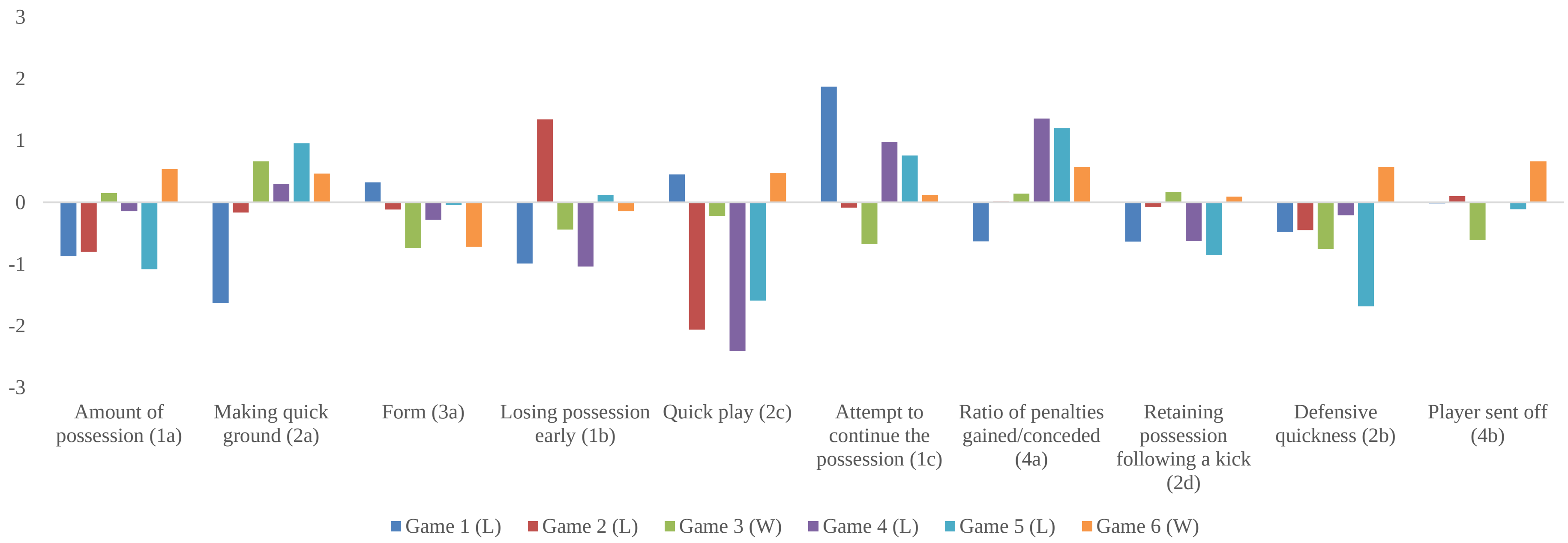

Figure 5.6 – St Helens' home performance on principal components scores in each preceding match in chronological order against top rated teams

Warrington had tended to perform better than league average on the amount of possession and quick plays, but had quite variable performance on the ratio of penalties gained/conceded, losing possession early and retaining possession following a kick (Figure 5.7).

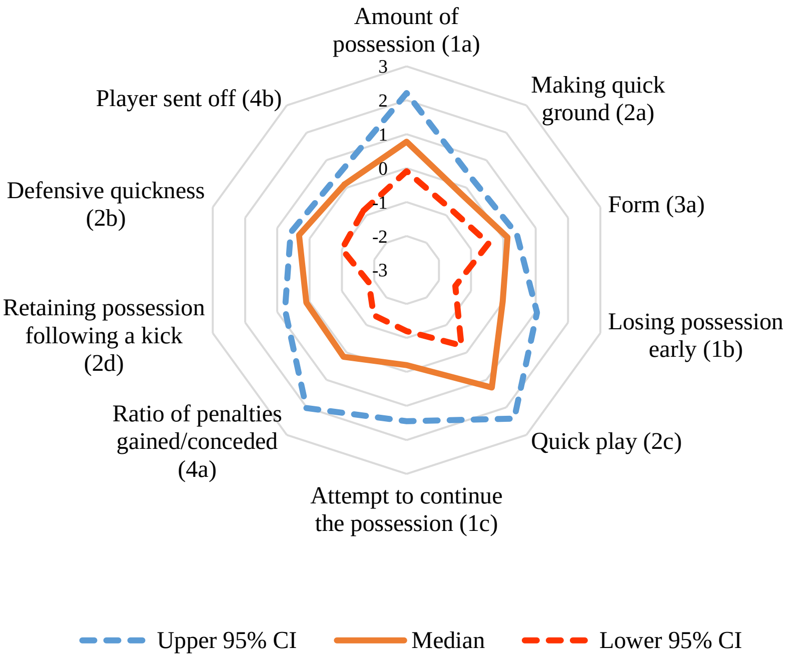

Figure 5.7. Warrington's away performance on principal components scores in 6 preceding matches against top rated teams

Warrington's away performances against top teams on a match to match basis suggested that their most recent performances were most consistent and at a high level for quick plays (Figure 5.8; the most historic performance had accounted for the variability seen in Figure 5.7). However, the variability for the ratio of penalties gained/conceded and retaining possession following a kick was a continuing issue for the team.

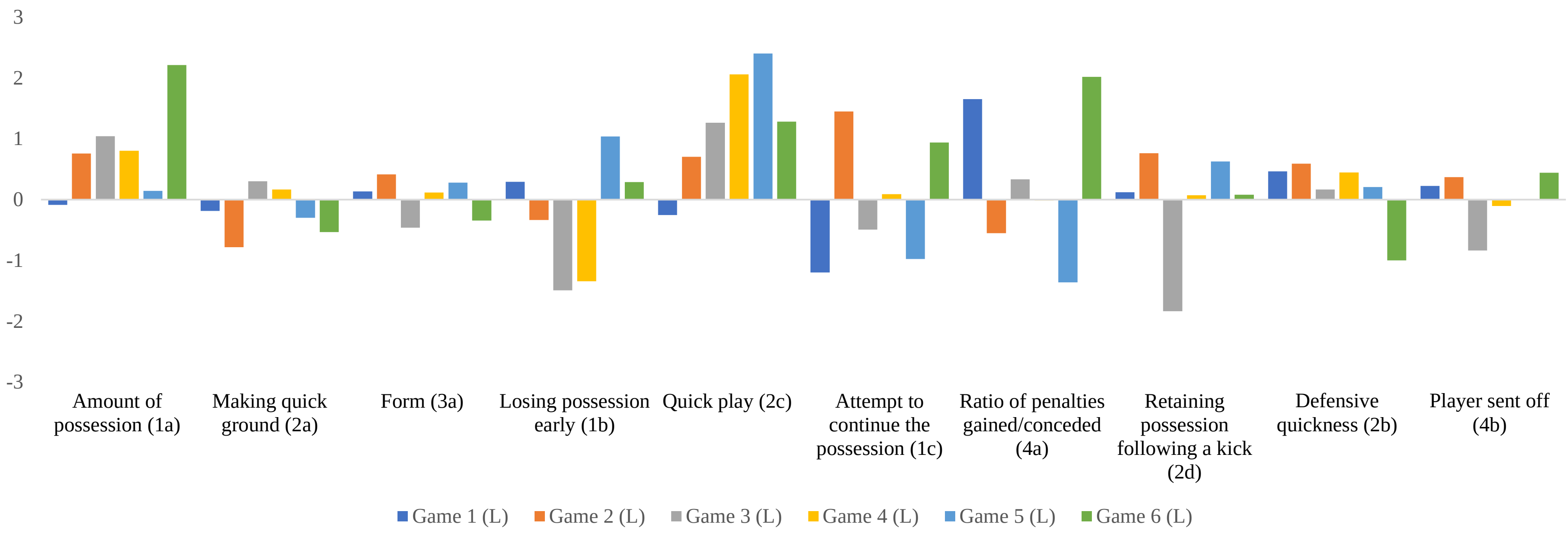

Figure 5.8. Warrington's away performance on principal components scores in each preceding match in chronological order against top rated teams

5.3.4 EXPONENTIAL SMOOTHING ALGORITHM

An exponential smoothing algorithm was utilised to predict performances on all 10 principle components for both teams upcoming match (Table 5.2), using all previous matches where both teams played in similar conditions i.e. same venue and opposition strength (St Helens, n=10 & Warrington, n=7). The relative value was calculated as St Helens predicted score minus Warrington's where a negative value indicated that Warrington was expected to outperform St Helens and vice versa.

Table 5.2 – Predicted principal component scores for upcoming match (St Helens and Warrington) including relative score

Team	Amount of possession (1a)	Making quick ground (2a)	Form (3a)	Losing possession early (1b)	Quick play (2c)	Attempt to continue the possession (1c)	Ratio of penalties gained/ conceded (4a)	Retaining possession following a kick (2d)	Defensive quickness (2b)	Player sent off (4b)
St Helens	-0.46	0.45	-0.27	-0.15	-0.63	0.37	0.62	-0.29	-0.53	0.09
Warrington	0.97	-0.47	-0.10	-0.60	1.39	0.18	0.10	-0.28	0.23	0.09
Relative	-1.43	0.92	-0.17	0.46	-2.02	0.19	0.52	0.00	-0.76	0.00

5.3.5 TWO PAGE PRE-MATCH SUMMARY

A two-page pre-match report was created from the viewpoint of an analyst working for Warrington, consisting of an opposition report (Figure 5.9) and team report (Figure 5.10). This report utilised form charts to display the median principal component scores with their 95% confidence intervals, from the previous 6 matches. The predicted performances were displayed using arrows to show the direction and estimation of the predicted performance in the upcoming match.

To provide a breakdown of the principal components determined to be most significant for the next match, z scores for the action variables that made the biggest contribution to the principal component score were displayed on radar charts for amount of possession and making ground. Losing possession early and quick plays only had three variables each and so were presented on one chart.

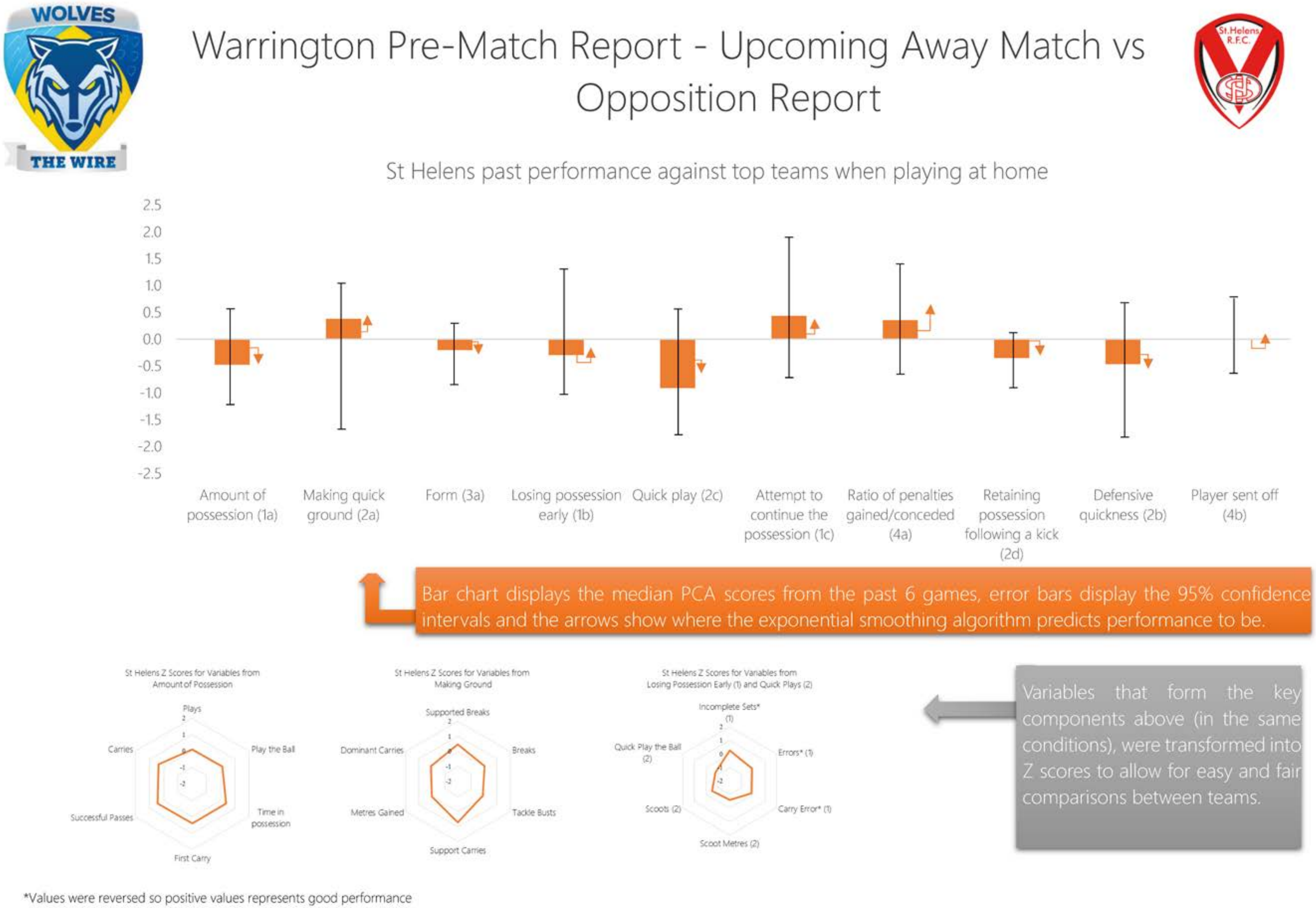

Figure 5.9. Opposition pre-match report sheet based on St Helens previous 6 games including predicted performance

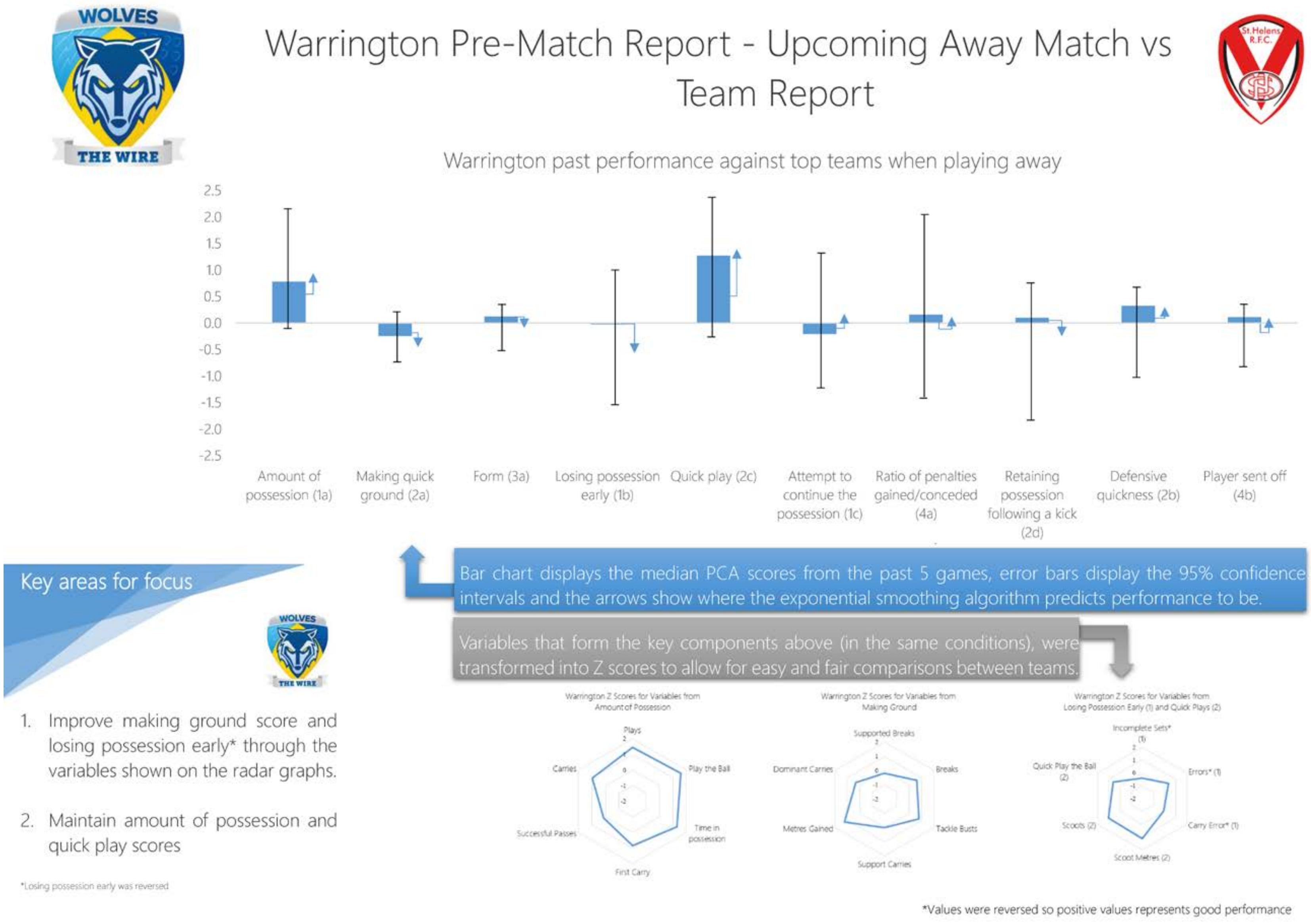

Figure 5.10. Team pre-match report sheet based on Warrington's previous 6 games including predicted performance.

5.3.6 POST-MATCH ANALYSIS

The coaches report (Figures 5.9 & 5.10) had suggested that Warrington generally performed better on amount of possession, quick plays and defensive quickness when playing away against top teams and that St Helens generally performed better on making quick ground, attempting to continue possession and ratio of penalties gained to conceded. These predicted values were made relative to each other, to try to predict which team would outperform the other (Table 5.2).

The actual and predicted performances (both relative, home minus away) were in same direction and reasonably close for the amount of possession, quick plays and defensive quickness (Figure 5.11). Predictions that suggested not much difference between the two teams were reasonably close although not always in the right direction.

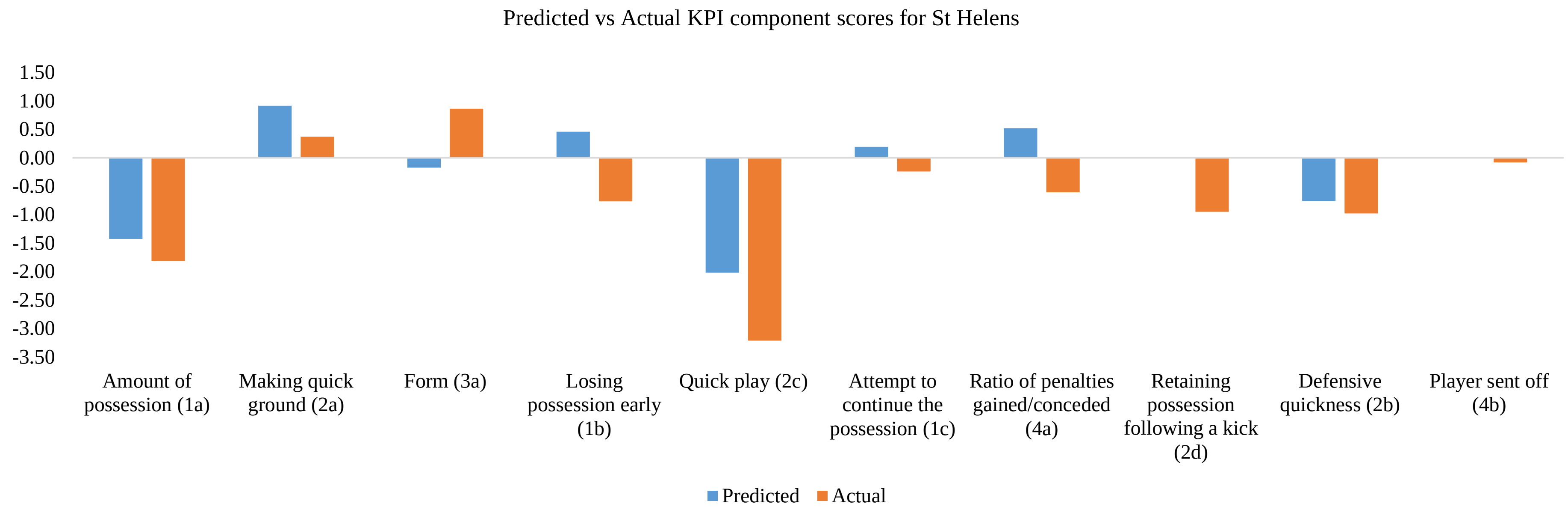

Figure 5.11. Predicted and actual principal component scores for St Helens vs Warrington.

5.4 DISCUSSION

Performance profiles have been suggested to enable a better understanding of how teams perform on performance indicators (Butterworth, O'Donoghue & Cropley, 2013) despite previous research using largely nomothetic approaches (James, Jones & Mellalieu, 2005; Liu, Gomez, Goncalves & Sampaio; Liu, Yi, Gimenez, Gomez & Lago-Penas, 2015; Taylor, Mellalieu & James, 2008; Vinson & Peters, 2016). Idiographic approaches were recommended for future studies in the previous chapter due to the large differences evident between the lower and upper boundaries for the odds ratio confidence intervals, which were attributed to the large sample size and inevitable variation between teams (Tucker, Mellalieu, James & Taylor, 2005). Therefore, this study aimed to; a) produce contextual performance profiles, by including the effect of match closeness, match venue and team quality, b) utilise an exponential smoothing algorithm to predict future component scores and c) produce methods and results that were relevant for practitioners.

When analysing the differences between the three levels of team quality (nomothetic profiles) it was apparent that the mean values displayed small differences between performances, however their associated standard deviations revealed the extent of the variations in performance, which were relatively large. Therefore, idiographic performance profiles were created for individual teams for each level of team quality, with clear differences within and between team performances, especially when considering the contextual variables. However, as the number of contextual variables increased, the number of cases reduced i.e. 6 different conditions for match venue and match closeness effectively reduced the sample 6-fold. Therefore, a large sample size is required to ensure adequate data is available in each condition, in this study with three seasons worth of data some conditions still had relatively small amounts of data. For example, Wigan had only 6 games where they played at home and lost by more than 12 points (unbalanced loss) over the three seasons. Stable profiles for most components were not achieved in these conditions, evidenced through the large differences observed between the lower and upper 95% confidence intervals on some principal components, especially when there were less games. The use of confidence intervals highlighted this issue, supporting the previous two chapter's findings, namely that the average is meaningless without its associated variation.

The exponential smoothing algorithm could provide a good indication of where team performances on principal components could be expected for some variables, as it was based on games that were played in the same conditions of the upcoming game i.e. according to opposition quality and match venue. However, using contextual/independent variables reduced the sample size, even within a within the very large data set used in this thesis, to the extent that statistical significance testing and "stable" performance profiles were difficult to achieve. To offset this problem another profile could be created for teams over several years, but many factors could influence individual performances such as league position and different styles of play due to managerial and playing staff changes. This could also be a reason why large variations were evident between confidence interval boundaries when larger sample were used in this study, although it could also be attributed to match specific conditions like referee decisions and player availability. Therefore, future studies could investigate how these factors influence performance, particularly when using data from multiple seasons.

The principal component scores utilised in this study were standardised to all other league performances, allowing for robust profiles to be created, due to the inherent context provided. Furthermore, the use of confidence intervals or similar approaches that can show the variation between performances, is suggested to put the average values into perspective. To utilise principal component analysis, it has been recommended that there should be a minimum of approximately 300 cases of data (Field, 2009), on the other hand, when analysing small samples, which could be argued to be more relevant and informative, less complex statistical methods or qualitative approaches are obtainable. However, the complexity and depth of the contextual variables often dictate the sample size required. Thus, the issue of 'reliability versus usefulness' arises. Therefore, a balance needs to be struck between utilising large sample sizes and complex statistics providing general results (quantitative) and having a small sample size with less complex statistics or qualitative approach, which could arguably provide more relevant and practical information.

An important use of performance profiles is the ability to analyse a team's strengths and weaknesses and furthermore to identify the same for an opposition. For example, the profiles for Wigan revealed that in unbalanced losses when playing away, they performed lower than the league average on attempts to continue possession and defensive quickness, whilst performing closer to league average on all other components. However, large variations for this team were evident through the 95% confidence intervals in unbalanced losses in both home and away games, which made it difficult to conclusively determine whether teams performed consistently in each condition. Despite these issues, the information gained from these profiles is argued to be more useful for coaches who may look for ways to improve performance by analysing profiles from unbalanced wins (and avoiding performances seen in unbalanced losses), compared to general results from nomothetic approaches.

To demonstrate the real-world relevance of the methodologies utilised in this study for practitioners (cf. Mackenzie and Cushion, 2013), a case study was presented which included a two-page pre-match summary, produced from the viewpoint of an analyst for Warrington. The case study presented a summary of both teams' performances over the previous 6 matches, which were selected if they met the same conditions as the upcoming match i.e. when playing against top teams and when home for St Helens and away for Warrington. An alternative approach could have utilised the analysis of both team's performances in unbalanced wins and losses to assess strengths and weaknesses. However, team quality and match venue was decided to provide suitable and relevant context to the data especially as teams can perform differently according to whether they play home or away (as evidenced through the idiographic performance profiles) and moreover, the exponential smoothing algorithm would not have been able to provide an appropriate prediction to the upcoming game unless it was based on similar conditions. Radar graphs were used to present the median performances on each principle component alongside their associated 95% confidence intervals, for both teams. This provided a clear overview of how they performed with form charts subsequently utilised to present a breakdown of performances on each principle component and to identify how team performances on principal components varied between games or if there were consistent improvements or erratic performances (explaining the difference between CI boundaries). Whilst it can inevitably become difficult to interpret the information-rich form chart, it provided a more detailed breakdown of performance than the radar graph alone.

The two-page pre-match report utilised form charts to display the average performances from their past 6 games (same conditions as upcoming match), to enable the inclusion of both the confidence intervals which were displayed through error bars and arrows which identified where the exponential smoothing algorithm predicted the upcoming performance to be. To aid the predictive ability of the algorithm it was calculated from all previous matches in the same condition. This allowed for an informative and unique form chart to be created which can be utilised by practitioners in their environments. In addition, a breakdown of four principle components (which were selected based on both teams contrasting performances on them) were presented in form charts using z scores to allow for multiple variables with different scales to be displayed on the same graph. The inclusion of the radar graphs on the pre-match report allowed for a better understanding of these components, by providing a breakdown of the variables that loaded highly on to them. This inclusion displayed a practical example of how to display supplementary information to aid practitioners understanding of how to improve their performance.

Several limitations were identified, firstly, the results shown are not necessarily transferable to other teams, however the caveat is the methodology can be utilised by individual teams when identifying their strengths and weaknesses as well as their opponents as demonstrated in the pre-match report. Secondly, match closeness utilised three categories, with balanced games encompassing wins or losses for games that resulted in 12 points or less points difference, however this did not take into consideration whether the team won or lost and therefore future investigations may wish to separate balanced games into balanced wins and balanced losses.

5.5 CONCLUSION

This study identified a unique method to utilise principle component scores for performance profiling. The use of contextual variables such as team quality, match venue and match closeness provided more informative results that could be utilised by coaches and performance analysts not only for rugby league, but for other sports. However future investigations may wish to separate balanced games into balanced wins and losses. Analysing teams from each level of team quality has been shown to enable individual differences to be analysed, despite large variations on principal component scores evident in certain scenarios where a small number of games had fallen under. However, team performances may never stabilise due to the unpredictability nature of sporting contests, in particular when analysing a complex game involving multiple players like rugby league. Despite these issues, it is clear that idiographic approaches presented in this chapter can be more relevant for practitioners, rather than analysing seemingly meaningless averages of all teams through nomothetic approaches, which provide little usefulness for coaches looking to improve their team's performances.

CHAPTER 6: GENERAL DISCUSSION

6.1 SUMMARY FINDINGS OF THE THESIS

This thesis aimed to provide a better understanding of professional rugby league through: a) creating clear and suitable definitions of PIs and KPIs, b) providing methodologies and results that could be utilised by practitioners and coaches, c) identifying reliable and robust PIs and KPIs, d) to score and graphically assess team performances on PIs and KPIs and e) utilise independent variables to provide context to data.

A key recommendation from the review of literature was that future performance indicator research should provide clear definitions of PIs and KPIs to enable a better understanding of variables that lead to success. This was due to previous research typically missing or providing unclear definitions, which could lead to misleading and confusing results. Therefore, justifications for why variables were deemed PIs were included in Study 1 and Study 2, in an attempt to avoid these issues. Another recommendation was that context should be provided to variables to avoid misleading accounts of performance. However, it was found that although making data relative to the opponent provided more context to the results by including both the home and away teams' performances on a single variable, complex regression analysis was unable to cope with a large number of variables which were not orthogonal. This was evidenced through peculiar results seen in Study 1 where variables that were shown as important in previous literature (e.g. line breaks) were excluded or through counterintuitive results i.e. more time in possession lead to a lower chance of winning. Furthermore, confidence intervals for odds ratios indicated large variations on performances on some variables, most likely due to the large sample size and inevitable variation between teams, suggesting that future research either include additional independent variables to add context and or utilise idiographic assessments of performances instead. Another limitation of the regression analyses was that it considered performances on variables in relation to one unit increases, which is appropriate for dichotomous variables, however results were problematic to understand when analysing scaled variables like metres gained, where it had been shown that teams performed 259 or more when they won. The use of CHIAD decision trees seemed to solve that issue whilst providing a simple description of the large dataset by explaining that teams who had outperformed their opponents by at least 259 metres, won 97.5% of the time. The decision trees had a lower predictive ability compared to the regression analyses, but this approach could be easier for coaches and practitioners to understand. Nonetheless, due to the removal of important variables that could be important to performance and the peculiar results evident in the regression analyses due to multicollinearity, dimension reduction techniques (like principal component analysis) was suggested to alleviate some of the issues identified by creating orthogonal components comprised of variables that explained the same variance in the dataset.

Therefore, Study 2 used principal component analysis (PCA) which reduced the dataset to just ten components, which explained 73.4% of the dataset. These ten principal components were grouped and categorised according to the proposed variance explained, resulting in four main groups; Possession (41.1%), Speed of play (20.9%), Form (6.0%) and Infringement (5.3%) with 26.7% of the variation left unexplained. The PCA created scores for each team performance on 10 components, which were analysed in logistic and linear regression models, utilising enter and backwards methods. Both methods were used to assess the suitability of stepwise methods when the dataset had already been reduced. Furthermore, decision trees identified key performance indicators due to their ability to summarise key variables albeit with a reduction of predictive ability as identified previously. Both the logistic and linear backwards methods retained the same 5 principal components with the linear regression retaining an additional component, defensive quickness, in its final model. Making quick ground was identified as a key performance indicator, with the component score increasing as performances on variables within the principal component, improved. However, large variations were evident for the confidence intervals (lower boundary 17.0 and upper boundary 22.8), which indicated that the large sample size and inevitable differences between teams were most likely contributing towards the variation. Therefore, it was suggested that whilst the large dataset can allow for sophisticated statistical analyses to take place, perhaps ideographic analysis could allow for more informative results rather than analysing somewhat meaningless averages which is inevitable when using large datasets. Furthermore, whilst stepwise regression models facilitate an easier-takeaway message. Some variables with low explanatory variables were removed, despite the significant differences that performances on these variables could make to match outcome particularly in balanced games, when they are performed.

The final study, addressed these issues by creating both nomothetic profiles (according to team quality) which used means and standard deviations, whilst ideographic profiles (for a single team from each level of team quality) used medians and their 95% confidence intervals as these assessments were created whilst accounting for match closeness and match venue. Large variations were evident on profiles, with some profiles only having several games worth of data in certain profiles due to the conditions being rarely met i.e. unbalanced wins when playing away for bottom rated teams. Some of these profiles could be deemed unstable (cf. Hughes, Evans & Wells. 2001), however it was suggested that performances may never stabilise (James, Mellalieu & Jones, 2005) due to the unpredictability of sport, especially when considering that rugby league is a complex and multi-faceted sport contested, by two teams of 13 players. Which inevitably leads to unique performances according to independent variables such as pitch size, weather, player availabilities, team quality and match venue. Therefore, it was suggested that these idiographic profiles provided informative results for coaches and practitioners compared to profiles created for groups of teams where individual traits can be lost. To demonstrate the use of contextual profiles, a case study was undertaken, comparing two top rated teams performances on principle components prior to a game. Furthermore, the use of an exponential smoothing algorithm was utilised to predict future performances on principle components based on their previous performances in the same conditions as the upcoming game. A practical example of a pre-match report was used to illustrate how profiles and an exponential smoothing algorithm could combined together and ultimately be used by practitioners, with simple modifications allowing for different types of variables to be analysed according to their particular sport.

6.2 KEY LIMITATIONS IDENTIFIED IN THIS THESIS

- This thesis only examined team performances and not individual players.
- Large sample size can hide differences between teams therefore analysing all teams can sometimes provide less meaningful information as opposed to analysing individual teams
- Data is from over three seasons some influencing factors such as managerial and or playing staff changes were not possible to identify or monitor from the dataset obtained.

6.3 ORIGINAL CONTRIBUTION TO KNOWLEDGE OF RUGBY LEAGUE PERFORMANCE

The original contributions to knowledge from this thesis are suggested to be:

1) Providing context to performance variables through the use of relative action variables and a combination of regression and machine learning methods to identify PIs and KPIs (refer to sections 3.2 and 4.2).
2) Produced clear definitions of how action variables, performance indicators and key performance indicators should be identified and differentiated between to allow for an easier understanding of performance (refer to section 3.1).
3) Producing robust measures of rugby league performance through principal component analysis which reduces large datasets to more manageable components of performances, eliminating multicollinearity issues which are usually associated with large sporting datasets (refer to sections 4.2 and 4.3)
4) Provided meaningful and interpretable results of team performances through standardised PCA scores, which enabled team performances to be compared to league standard, with the added combination of statistical methods like regression analysis and machine learning decision trees (refer to sections 4.2 and 4.3).
5) Suitable methods of assessing form in rugby league such as cumulative league form and past 5 game form were identified and shown to be important to predicting rugby league performance, which are suggested to be more indicative of team quality than using final league position alone (refer to sections 3.2, 3.3, 4.2 and 4.3).
6) The use of ideographic and nomothetic performance profiles for rugby league teams, using standardised principle component scores, with match closeness

and match venue is suggested to provide meaningful and contextual assessments of performances (refer to sections 5.3 and 5.4).

7) Exponential smoothing was identified and used as a suitable tool for predicting future performances in rugby league on principal components (refer to sections 5.3.4 to 5.3.6).

6.4 SUMMARY OF PRACTICAL IMPLICATIONS FOR PRACTITIONERS AND COACHES

Practical implications for practitioners:

- By making data relative to opposition, better context is provided on performance variables through a clear understanding of whether the team outperformed (positive value) or underperformed (negative value).
- When assessing a large number of variables the issue of multicollinearity is likely, affecting statistical methods like regression. Therefore, appropriate dimension reduction techniques should be employed which can produce orthogonal variables, thereby allowing sophisticated analysis to take place.
- Whilst regression analysis can provide a robust assessment of whether performance variables can predict match outcome (logistic) and point's difference (linear) the results are not always easily interpretable by practitioners who may not be statistically minded. Therefore, decision trees can simplify the results and could be used to explain performance to coaches.
- When using regression analysis, the beta coefficient or odds ratios provide information on how the chances of success can increase or decrease by a one unit increase on the analysed variable. This is not always an appropriate method when dealing with scaled variables like metres gained where teams

typically perform 259 or more than their opponent when they win. Therefore, the use of decision trees is suggested to provide more interpretable results.

- When producing performance profiles, the use of match closeness and match venue provide relevant and informative context to performances which can be used to identify and compare strengths and weaknesses of teams.
- Ideographic assessments of performance are suggested to be more relevant for practitioners due to the rich information that can be understood as opposed to less informative generalised assessments of performance through nomothetic approaches.
- A simple exponential smoothing algorithm can be utilised to provide an indication of where future performances may reach. This could be used in pre-match reports, alongside a summary of previous performances.

Practical implications for rugby league coaches

- Principal component analysis identified four key areas of performance: possession, speed of play, form and infringements. Coaches can investigate the principle components that form these categories, in order to improve their teams performance.
- It is suggested that improved performances on all 10 components, can lead to a better chance of winning. Therefore coaches can utilise this information to inform their training session and tactics.
- Decision tree analysis revealed a simple explanation of performance:
    - Teams that improve performances on making ground were 72.7% more likely to win, increasing to 91.6% when outperforming on amount of possession.

    - If teams underperformed on making ground, they were only 29.8% likely to win, increasing to 43.3% if teams improved quick plays
- Coaches should focus on the processes of outcomes i.e. making quick ground from the amount of possession a team has. This can lead to better chances of winning as evidenced from the decision tree results.

6.5 CONCLUSION

This thesis attempted to address the ‘theory to practice’ gap paradox, which has remained elusive so far. Mackenzie and Cushion (2013) suggested the gap has been created due to performance analysis researchers not always asking relevant questions in their investigations and producing methodologies which have no relevance to practitioners. They alluded that a balance should be struck between answering real-world issues perhaps through simple and relevant questions and scientifically rigorous investigations that lack usefulness or transferability. Science and practice has so far been mutually exclusive, however this thesis attempted to address this issue although a conclusive solution seemed elusive. This thesis culminated in the use of ideographic assessments of performance through performance profiles which arguably provided more informative and relevant assessments for practitioners compared to nomothetic profiles where individual differences can be lost. Therefore, future investigations should consider the depth of the analysis undertaken and ensure that relevant context is provided in order to try and retain individual traits in performances. The use of average values which inform the end-reader of general principles relating to the sport analysed has been shown throughout this thesis to be less informative, especially if presented without their associated variation. It would consequently be logical to assume that teams who are interested in making improvements to their performance would utilise idiographic methodologies as demonstrated in this thesis.

6.6 FUTURE RESEARCH DIRECTIONS

Several future directions could expand on the themes developed in this thesis:

1. Utilise principal components to create a team rating system.
2. Determine performance variables that best determine individual player contributions and hence create a player rating system
3. Identify and develop rigorous methodologies for performance analysis research that addresses the practice to theory paradox identified by Mackenzie and Cushion (2013).

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APPENDICES

Appendix 3.1 Ethical Approval Letter for Studies 1 and 2

Middlesex University
London Sport Institute

School of Health and Education
The Burroughs
London NW4 4BT

www.mdx.ac.uk
Main switchboard:
020 8411 5000

To: Nimai Parmar

Date: Monday, 12 May 2014

Dear Nimai

Re: Application 219 'Team Performance Indicators in Professional Rugby League'.'
Supervisor: Prof Nic James Category: A1

The London Sport Institute Ethics Sub-Committee considered your application. On behalf of the committee, I am pleased to inform you that your application has been approved. However, please note that the committee must be informed if any changes in the protocol need to be made at any stage.

I wish you all the very best with your project. The committee will be delighted to receive a copy of the final report.

Yours sincerely

Dr. Rhonda Cohen
Chair of Ethics Sub-committee (London Sport Institute)

Appendix 3.2 –Team quality rating based on the previous 3 years' final league positions for Super League teams from 2009 to 2014

Team	Team quality rating	Average from past 3 years	2014	2013	2012	2011	2010	2009
Bradford Bulls	Middle	10	13	9	9	10	10	9
Castleford Tigers	Middle	10	4	12	13	9	9	7
Catalans Dragons	Middle	6	7	7	4	6	14	8
Huddersfield Giants	Top	4	3	1	7	4	5	3
Hull FC	Middle	8	11	6	6	8	6	12
Hull Kingston Rovers	Middle	9	9	8	10	7	7	4
Leeds Rhinos	Middle	5	6	3	5	5	4	1
London Broncos	Bottom	13	14	13	12	12	13	11
North Wales Crusaders*	N/A	N/A	Relegated	Relegated	Relegated	14	8	14
Salford Red Devils	Bottom	12	10	14	11	11	12	13
St Helens	Top	3	1	5	3	3	2	2
Wakefield Wildcats	Middle	10	12	11	8	13	11	5
Warrington Wolves	Top	3	5	2	2	1	3	10
Widnes	Bottom	11	8	10	14	15	15	15
Wigan Warriors	Top	2	2	4	1	2	1	6

*Relegated

Appendix 3.3 Correlation coefficients with points difference for 2012-13 seasons

Variable	r
Cumulative league form	.375
5 game form	.349
Average of past 3 season's league positions	-.422
Previous season final league position	-.519
Current season final league position	-.588
Score first	.412
Plays	.623
Time in possession	.586
Total sets	.753
Completed sets	.710
Incomplete sets	-.013
Tackles	-.531
Missed tackles	-.706
Kicks	.188
Retained kicks	.282
Forty20 kick	.109
Play the ball (PTB)	.540
Quick PTB	.362
Carries	.644
Metres gained	.850
Breaks	.829
Total offloads	.196
Successful offloads	.255
Unsuccessful offloads	-.056
Errors	-.169
Penalties conceded	-.263
Support carries	.511
Dominant carry	.646
Carry error	-.072
Tackle bust	.708
Penalty Won	.136
Supported break	.591
Successful pass	.455
Unsuccessful pass	.675
Total passes	.517
Successful collections	.644
Failed collections	-.166
Offside 10m	.036
Offside marker	-.006
Sin bin	-.063
Sent off	.052
First carry	.444
First carry metres	.647
Scoot	.327
Scoot metres	.342

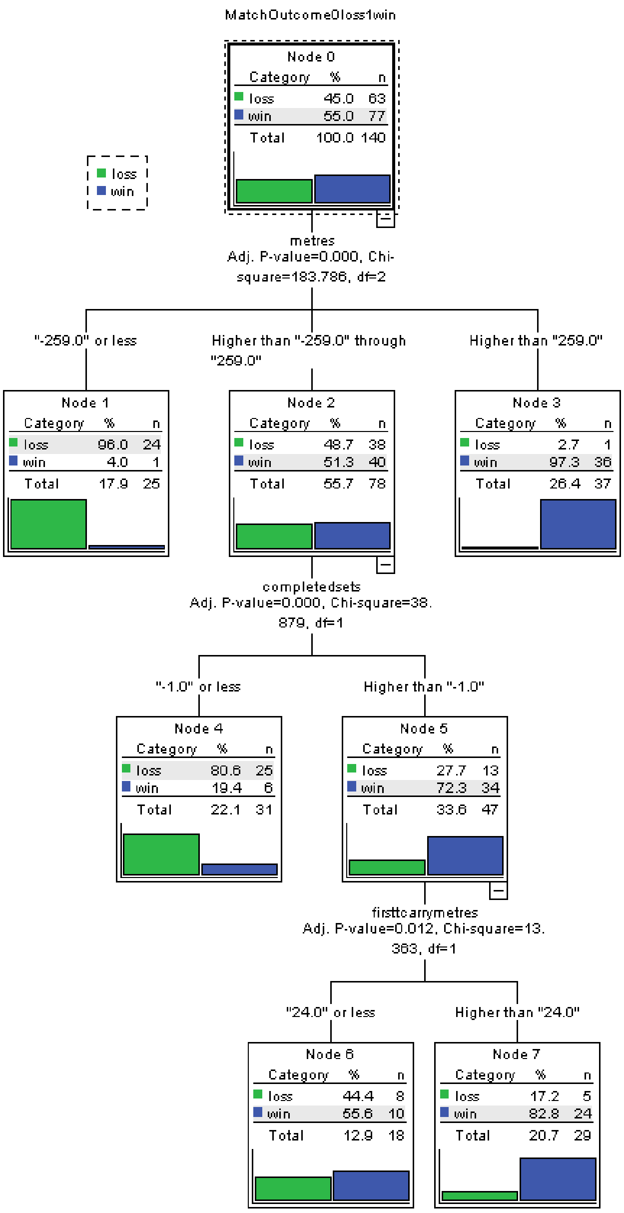
Appendix 3.4 –Logistic regression model from 2014 data (cross validation model)

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1	Previous season final league position	.029	.085	.115	1	.735	1.029	.872	1.214
	Current season final league position	-.187	.095	3.851	1	.050	.829	.688	1.000
	Score first	-.102	.729	.020	1	.889	.903	.217	3.766
	Time in possession	.004	.002	2.671	1	.102	1.004	.999	1.008
	Completed sets	.342	.084	16.719	1	.000	1.408	1.195	1.658
	Metres gained	.012	.003	15.756	1	.000	1.012	1.006	1.018
	Dominant carry	-.050	.067	.567	1	.452	.951	.834	1.084
	Successful pass	-.056	.016	11.764	1	.001	.945	.915	.976
	Successful collections	.011	.063	.029	1	.864	1.011	.893	1.144
	Scoot	.050	.080	.399	1	.527	1.052	.900	1.229
	Scoot metres	-.023	.010	5.120	1	.024	.977	.958	.997
	Constant	.667	.501	1.771	1	.183	1.948		

Appendix 3.5 – Logistic regression model from 2014 data (cross validation model)

	Observed	Predicted		Percentage correct
		Loss	Win	
2012-2013	Loss	144	14	91.1
	Win	19	188	90.8
	Overall percentage			91.0
2014 (cross-validation)	Loss	58	8	87.9
	Win	6	108	94.7
	Overall percentage			92.2

Appendix 3.6 –Exhaustive CHAID decision trees using 25% of the data (test sample)



Appendix 4.1 rotated component matrix from PCA analysis

Variables	Component									
	1	2	3	4	5	6	7	8	9	10
Plays	.911									
Play the ball (PTB)	.904									
Tackles	-.884									
Time in possession	.849									
First carry	.837									
Successful passes	.832									
Carries	.828									
Total passes	.820									
First carry metres	.754									
Total sets	.719									
Completed sets	.676			-.456						
Metres gained	.626	.559								
Retained kicks	.575							.493		
Successful collections	.522									
Supported break		.796								
Breaks		.786								
Tackle busts		.695								
Missed tackles		-.693								
Support carries		.669				.500				
Unsuccessful passes		.661								
Dominant carry	.401	.509								

Appendix 4.1 rotated component matrix from PCA analysis (continued)

Variables	Component									
	1	2	3	4	5	6	7	8	9	10
Score first										
Cumulative league form			.858							
Current season final league position			.838							
Previous season final league position			.789							
5 game form			.781							
Average of past 3 season's league positions			.754							
Incomplete sets				.880						
Errors				.838						
Carry error				.713						
Kicks	.462			-.634						
Scoot metres					.898					
Scoot					.880					
PTB					.559					
Total offloads						.924				
Successful offloads						.827				
Unsuccessful offloads						.682				
Penalties conceded							-.728			
Offside marker							-.584			
Penalty won							.568			
Forty20 kick								.732		
Offside 10m									.737	

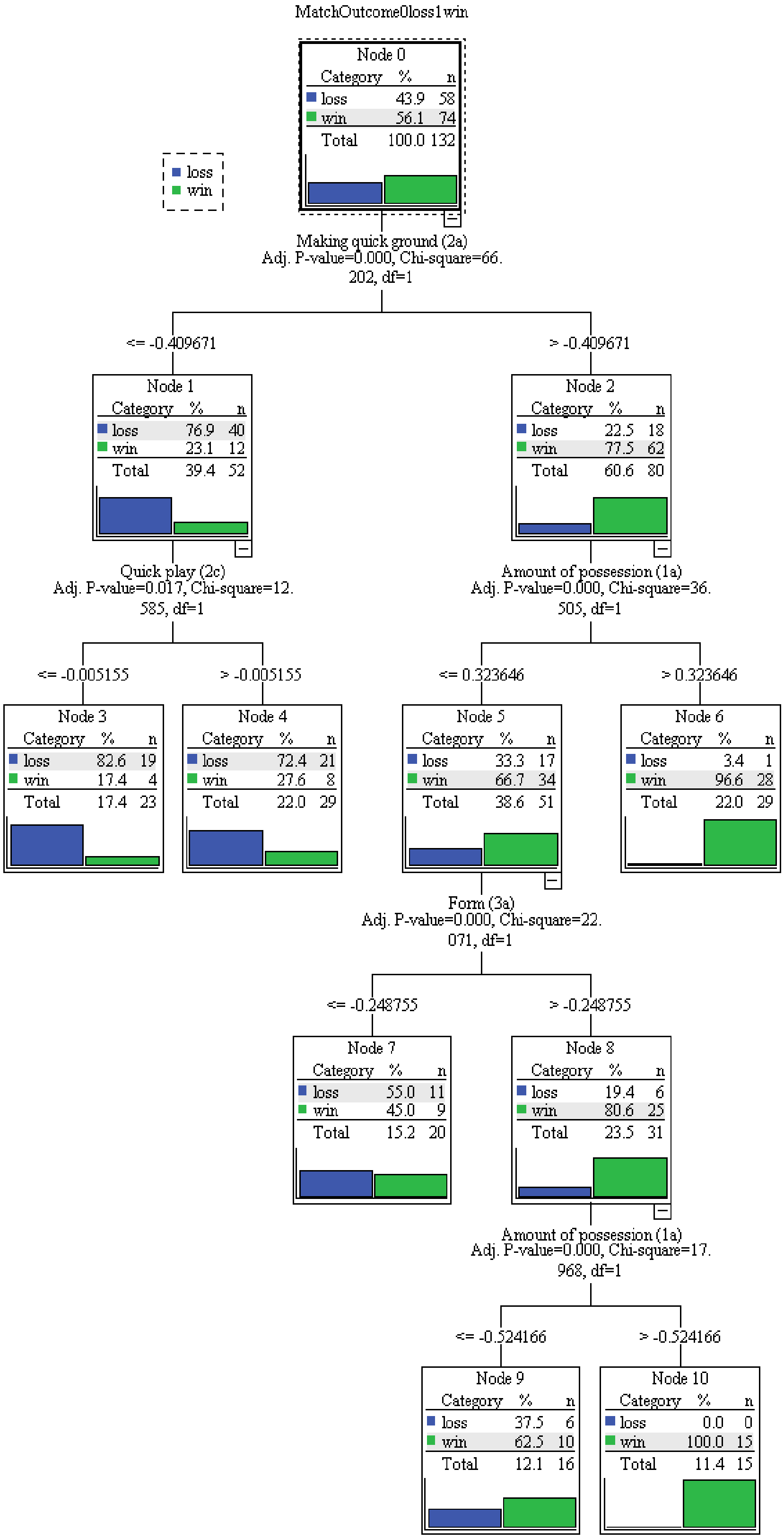
Appendix 4.1 Rotated component matrix from PCA analysis (continued)

Variables	Component 1	2	3	4	5	6	7	8	9	10
Failed collections									-.499	
Sent off										.852
Sin bin										

Appendix 4.2 Total variance explained from PCA

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.671	32.602	32.602	14.671	32.602	32.602	9.815	21.812	21.812
2	5.206	11.569	44.172	5.206	11.569	44.172	5.033	11.185	32.997
3	2.719	6.043	50.215	2.719	6.043	50.215	4.254	9.452	42.449
4	2.303	5.117	55.332	2.303	5.117	55.332	3.063	6.807	49.256
5	1.921	4.270	59.601	1.921	4.270	59.601	2.848	6.329	55.585
6	1.504	3.341	62.942	1.504	3.341	62.942	2.672	5.939	61.524
7	1.419	3.153	66.095	1.419	3.153	66.095	1.737	3.860	65.383
8	1.188	2.640	68.736	1.188	2.640	68.736	1.278	2.840	68.223
9	1.078	2.396	71.132	1.078	2.396	71.132	1.214	2.697	70.921
10	1.023	2.274	73.406	1.023	2.274	73.406	1.118	2.485	73.406

Appendix 4.3 Exhaustive CHAID decision trees from 25% of the data (test sample)



Appendix 5.1 Ethical approval letter for Study 3

Middlesex University London

London Sport Institute REC

The Burroughs
Hendon
London NW4 4BT

Main Switchboard: 0208 411 5000

11/08/2016

APPLICATION NUMBER: 0645

Dear Nimai Chandra Parmar

Re your application title: Profiling and Rating Team and Individuals Performances in Professional Rugby League

Supervisor: Nic James

Thank you for submitting your application. I can confirm that your application has been given approval from the date of this letter by the London Sport Institute REC.

Please ensure that you contact the ethics committee if any changes are made to the research project which could affect your ethics approval.

The committee would be pleased to receive a copy of the summary of your research study when completed.

Please quote the application number in any correspondence.

Good luck with your research.

Yours sincerely

Dr rhonda Cohen

London Sport Institute REC

Page 1 of 1

Appendix 5.2.1 Conditional formatting example for a team in Unbalanced Wins

	1 Amount of possession	2 Making quick ground	3 Form	4 Losing possession early	5 Quick play
Home	0.69	0.57	1.10	0.18	0.13
Away	1.34	0.93	0.75	-0.01	0.34

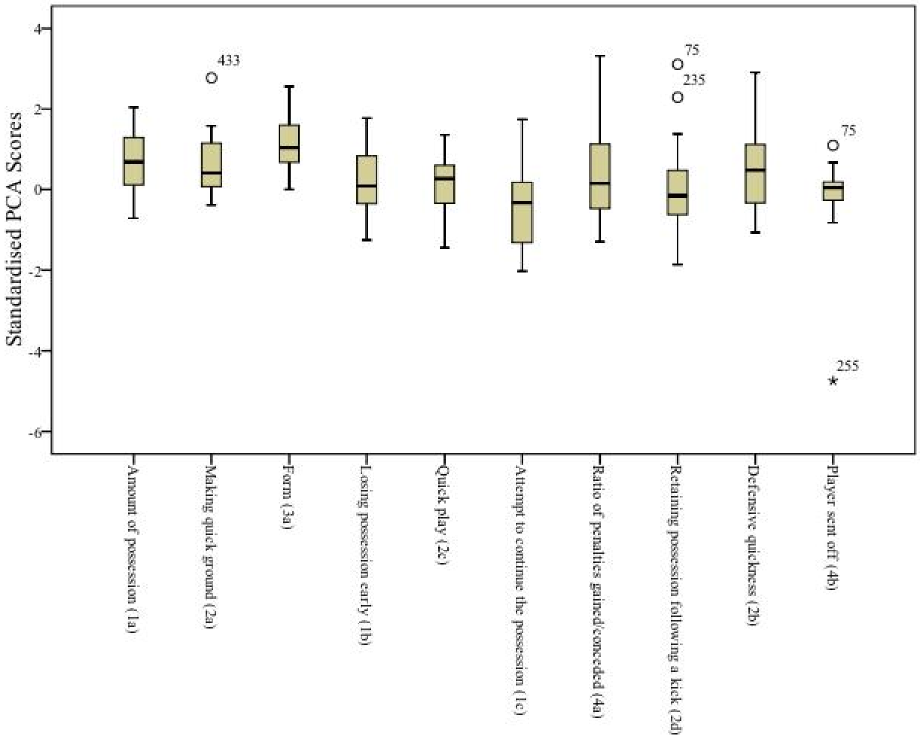
Appendix 5.2.2 Conditional formatting example for a team in Balanced Games

	1 Amount of possession	2 Making quick ground	3 Form	4 Losing possession early	5 Quick play
Home	0.02	-0.02	0.69	-0.36	-0.12
Away	0.49	-0.36	1.07	-0.26	-0.32

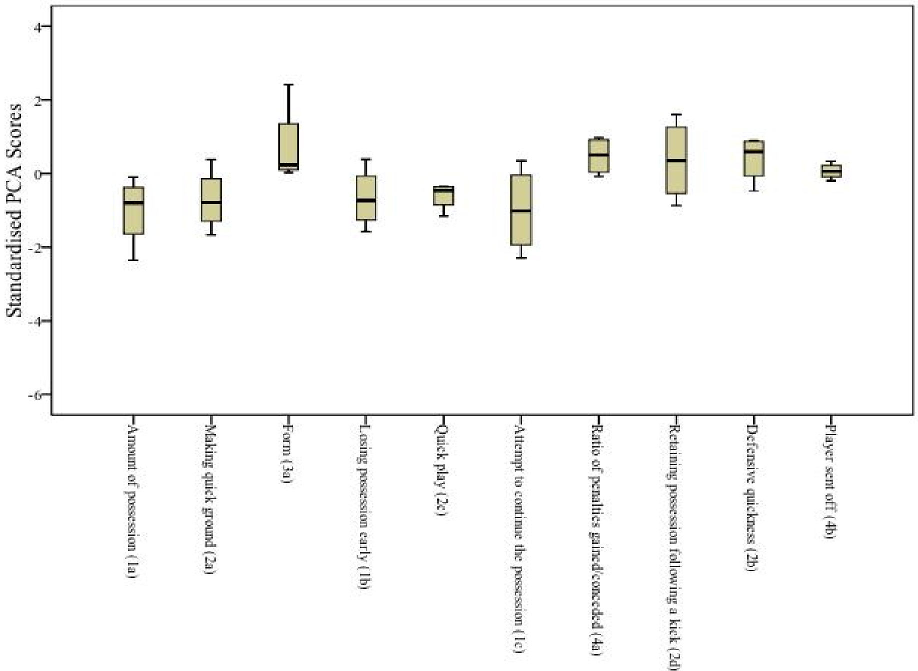
Appendix 5.2.3 Conditional formatting example for a team in Unbalanced Losses

	1 Amount of possession	2 Making quick ground	3 Form	4 Losing possession early	5 Quick play
Home	-1.01	-0.72	0.73	-0.66	-0.61
Away	-0.76	-0.44	0.90	-0.72	0.25

Appendix 5.3. Box plot for Wigan on principal components when playing at home in unbalanced wins (n=22)



Appendix 5.4. Box plot for Wigan on principal components when playing at home in unbalanced losses (n=6)



Appendix 5.5. Root mean square error values for exponential smoothing weightings for St Helens

Weighting	Amount of possession (1a)	Making quick ground (2a)	Form (3a)	Losing possession early (1b)	Quick play (2c)	Attempt to continue the possession (1c)	Ratio of penalties gained/ conceded (4a)	Retaining possession following a kick (2d)	Defensive quickness (2b)	Player sent off (4b)
0.1	0.96	1.18	0.39	1.62	1.95	1.42	0.88	0.64	0.67	1.97
0.2	0.96	1.04	0.41	1.38	1.70	1.32	0.86	0.59	0.66	1.87
0.3	0.98	0.97	0.42	1.28	1.59	1.29	0.85	0.57	0.68	1.86
0.4	1.00	0.95	0.44	1.25	1.55	1.30	0.86	0.56	0.70	1.87
0.5	1.04	0.96	0.46	1.26	1.56	1.32	0.88	0.56	0.73	1.91
0.6	1.07	0.97	0.48	1.29	1.60	1.35	0.91	0.57	0.77	1.96
0.7	1.10	1.00	0.50	1.34	1.66	1.39	0.93	0.57	0.80	2.02
0.8	1.13	1.04	0.53	1.40	1.73	1.44	0.96	0.57	0.84	2.10
0.9	1.17	1.07	0.56	1.47	1.83	1.49	1.00	0.57	0.89	2.19

Appendix 5.6. Root mean square error values for exponential smoothing weightings for Warrington

Weighting	Amount of possession (1a)	Making quick ground (2a)	Form (3a)	Losing possession early (1b)	Quick play (2c)	Attempt to continue the possession (1c)	Ratio of penalties gained/ conceded (4a)	Retaining possession following a kick (2d)	Defensive quickness (2b)	Player sent off (4b)
0.1	0.80	1.03	0.38	1.12	2.16	1.06	1.30	0.98	0.17	0.47
0.2	0.82	0.89	0.38	1.14	1.85	1.10	1.35	1.00	0.18	0.48
0.3	0.85	0.81	0.40	1.17	1.59	1.16	1.41	1.03	0.18	0.49
0.4	0.88	0.77	0.41	1.21	1.39	1.22	1.47	1.07	0.19	0.50
0.5	0.91	0.75	0.43	1.25	1.22	1.29	1.54	1.12	0.20	0.52
0.6	0.94	0.74	0.45	1.28	1.08	1.36	1.61	1.17	0.21	0.54
0.7	0.97	0.73	0.47	1.31	0.97	1.44	1.68	1.22	0.22	0.56
0.8	1.00	0.73	0.49	1.33	0.88	1.53	1.75	1.28	0.23	0.58
0.9	1.03	0.73	0.51	1.34	0.80	1.63	1.84	1.34	0.24	0.61

Appendix 5.7. Exponential smoothing for making quick ground component - St Helens

	Principal component Score 2	Predicted Score 2	Error	Absolute error	Square error
Match 1	-1.20				
Match 2	-1.11	-1.20	0.08	0.08	0.01
Match 3	-0.18	-1.16	0.98	0.98	0.96
Match 4	0.78	-0.77	1.55	1.55	2.41
Match 5	-1.63	-0.15	-1.48	1.48	2.19
Match 6	-0.17	-0.74	0.57	0.57	0.33
Match 7	0.66	-0.51	1.18	1.18	1.38
Match 8	0.30	-0.04	0.34	0.34	0.12
Match 9	0.96	0.09	0.86	0.86	0.75
Match 10	0.47	0.44	0.03	0.03	0.00
Predicted		0.45			
Average			0.46	0.79	0.90
RMSE					0.95

Appendix 5.8 Exponential smoothing for Form component - St Helens

	Principal component Score 3	Predicted Score 3	Error	Absolute error	Square error
Match 1	-0.26				
Match 2	-0.51	-0.26	-0.25	0.25	0.06
Match 3	0.32	-0.28	0.60	0.60	0.36
Match 4	-0.42	-0.22	-0.19	0.19	0.04
Match 5	0.32	-0.24	0.56	0.56	0.32
Match 6	-0.11	-0.19	0.07	0.07	0.01
Match 7	-0.74	-0.18	-0.56	0.56	0.31
Match 8	-0.28	-0.24	-0.05	0.05	0.00
Match 9	-0.04	-0.24	0.20	0.20	0.04
Match 10	-0.72	-0.22	-0.50	0.50	0.25
Predicted		-0.27			
Average			-0.01	0.33	0.15
RMSE					0.39

Appendix 5.9. Exponential smoothing for Losing possession early component - St Helens

	Principal component Score 4	Predicted Score 4	Error	Absolute error	Square error
Match 1	1.95				
Match 2	-0.54	1.95	-2.49	2.49	6.21
Match 3	1.11	0.96	0.16	0.16	0.03
Match 4	0.33	1.02	-0.68	0.68	0.47
Match 5	-0.99	0.75	-1.74	1.74	3.02
Match 6	1.34	0.05	1.29	1.29	1.67
Match 7	-0.44	0.57	-1.01	1.01	1.02
Match 8	-1.04	0.16	-1.20	1.20	1.45
Match 9	0.11	-0.32	0.43	0.43	0.19
Match 10	-0.15	-0.14	0.00	0.00	0.00
Predicted		-0.15			
Average			-0.58	1.00	1.56
RMSE					1.25

Appendix 5.10 Exponential smoothing for Quick Play component - St Helens

	Principal component Score 5	Predicted Score 5	Error	Absolute error	Square error
Match 1	1.62				
Match 2	-0.33	1.62	-1.95	1.95	3.79
Match 3	1.67	0.84	0.83	0.83	0.68
Match 4	-0.70	1.17	-1.87	1.87	3.51
Match 5	0.45	0.42	0.03	0.03	0.00
Match 6	-2.06	0.43	-2.49	2.49	6.21
Match 7	-0.22	-0.56	0.34	0.34	0.12
Match 8	-2.40	-0.43	-1.97	1.97	3.90
Match 9	-1.59	-1.22	-0.38	0.38	0.14
Match 10	0.47	-1.37	1.84	1.84	3.38
Predicted		-0.63			
Average			-0.62	1.30	2.41
RMSE					1.55

Appendix 5.11 Exponential smoothing for Attempt to continue the possession component - St Helens

	Principal component Score 6	Predicted Score 6	Error	Absolute error	Square error
Match 1	1.65				
Match 2	0.52	1.65	-1.13	1.13	1.28
Match 3	-0.33	1.31	-1.64	1.64	2.70
Match 4	-1.45	0.82	-2.27	2.27	5.14
Match 5	1.87	0.14	1.74	1.74	3.01
Match 6	-0.09	0.66	-0.75	0.75	0.56
Match 7	-0.68	0.43	-1.11	1.11	1.23
Match 8	0.98	0.10	0.88	0.88	0.77
Match 9	0.76	0.36	0.39	0.39	0.16
Match 10	0.11	0.48	-0.37	0.37	0.14
Predicted		0.37			
Average			-0.47	1.14	1.66
RMSE					1.29

Appendix 5.12. Exponential smoothing for Ratio of penalties gained/conceded component- St Helens

	Principal component Score 7	Predicted Score 7	Error	Absolute error	Square error
Match 1	-0.16				
Match 2	-1.23	-0.16	-1.07	1.07	1.14
Match 3	0.90	-0.48	1.38	1.38	1.91
Match 4	0.55	-0.07	0.62	0.62	0.38
Match 5	-0.63	0.12	-0.75	0.75	0.56
Match 6	0.01	-0.11	0.12	0.12	0.01
Match 7	0.14	-0.07	0.21	0.21	0.04
Match 8	1.36	-0.01	1.37	1.37	1.86
Match 9	1.20	0.40	0.80	0.80	0.64
Match 10	0.57	0.64	-0.07	0.07	0.00
Predicted		0.62			
Average			0.29	0.71	0.73
RMSE					0.85

Appendix 5.13 Exponential smoothing for retaining possession following a kick component - St Helens

	Principal component Score 8	Predicted Score 8	Error	Absolute error	Square error
Match 1	0.28				
Match 2	0.14	0.28	-0.14	0.14	0.02
Match 3	-0.83	0.22	-1.05	1.05	1.11
Match 4	-0.76	-0.20	-0.57	0.57	0.32
Match 5	-0.64	-0.42	-0.21	0.21	0.05
Match 6	-0.07	-0.51	0.44	0.44	0.19
Match 7	0.17	-0.33	0.50	0.50	0.25
Match 8	-0.63	-0.13	-0.49	0.49	0.24
Match 9	-0.85	-0.33	-0.52	0.52	0.27
Match 10	0.09	-0.54	0.63	0.63	0.40
Predicted		-0.29			
Average			-0.16	0.51	0.32
RMSE					0.56

Appendix 5.14 Exponential smoothing for Defensive quickness component - St Helens

	Principal component Score 9	Predicted Score 9	Error	Absolute error	Square error
Match 1	-1.01				
Match 2	-0.63	-1.01	0.37	0.37	0.14
Match 3	-0.39	-0.93	0.54	0.54	0.29
Match 4	-0.59	-0.82	0.23	0.23	0.05
Match 5	-0.48	-0.78	0.30	0.30	0.09
Match 6	-0.45	-0.72	0.27	0.27	0.07
Match 7	-0.76	-0.66	-0.09	0.09	0.01
Match 8	-0.21	-0.68	0.47	0.47	0.22
Match 9	-1.68	-0.59	-1.10	1.10	1.20
Match 10	0.57	-0.81	1.38	1.38	1.90
Predicted		-0.53			
Average			0.26	0.53	0.44
RMSE					0.66

Appendix 5.15 Exponential smoothing for Player sent off component - St Helens

	Principal component Score 10	Predicted Score 10	Error	Absolute error	Square error
Match 1	1.45				
Match 2	-4.01	1.45	-5.46	5.46	29.81
Match 3	-0.03	-0.19	0.16	0.16	0.02
Match 4	-0.37	-0.14	-0.23	0.23	0.05
Match 5	-0.02	-0.21	0.19	0.19	0.04
Match 6	0.10	-0.15	0.26	0.26	0.07
Match 7	-0.61	-0.08	-0.54	0.54	0.29
Match 8	0.00	-0.24	0.24	0.24	0.06
Match 9	-0.11	-0.17	0.05	0.05	0.00
Match 10	0.66	-0.15	0.81	0.81	0.66
Predicted		0.09			
Average			-0.50	0.88	3.44
RMSE					1.86

Appendix 5.16 Exponential smoothing for Amount of possession component - Warrington

	Principal component Score 1	Predicted Score 1	Error	Absolute error	Square error
Match 1	1.03				
Match 2	-0.09	1.03	-1.12	1.12	1.25
Match 3	0.76	0.92	-0.16	0.16	0.02
Match 4	1.04	0.90	0.14	0.14	0.02
Match 5	0.80	0.92	-0.11	0.11	0.01
Match 6	0.14	0.90	-0.76	0.76	0.58
Match 7	2.21	0.83	1.39	1.39	1.92
Predicted		0.97			
Average			-0.10	0.61	0.63
RMSE					0.80

Appendix 5.17 Exponential smoothing for Making quick ground component - Warrington

	Principal component Score 2	Predicted Score 2	Error	Absolute error	Square error
Match 1	0.98				
Match 2	-0.19	0.98	-1.17	1.17	1.36
Match 3	-0.78	0.05	-0.83	0.83	0.68
Match 4	0.30	-0.62	0.92	0.92	0.85
Match 5	0.17	0.12	0.05	0.05	0.00
Match 6	-0.30	0.16	-0.46	0.46	0.21
Match 7	-0.53	-0.21	-0.32	0.32	0.10
Predicted		-0.47			
Average			-0.30	0.62	0.53
RMSE					0.73

Appendix 5.18 Exponential smoothing for Form component - Warrington

	Principal component Score 3	Predicted Score 3	Error	Absolute error	Square error
Match 1	-0.19				
Match 2	0.14	-0.19	0.32	0.32	0.10
Match 3	0.42	-0.16	0.57	0.57	0.33
Match 4	-0.46	-0.10	-0.36	0.36	0.13
Match 5	0.11	-0.13	0.25	0.25	0.06
Match 6	0.28	-0.11	0.39	0.39	0.15
Match 7	-0.34	-0.07	-0.27	0.27	0.07
Predicted		-0.10			
Average			0.15	0.36	0.14
RMSE					0.38

Appendix 5.19 Exponential smoothing for Losing possession early component - Warrington

	Principal component Score 4	Predicted Score 4	Error	Absolute error	Square error
Match 1	-0.95				
Match 2	0.29	-0.95	1.24	1.24	1.54
Match 3	-0.33	-0.82	0.49	0.49	0.24
Match 4	-1.49	-0.77	-0.72	0.72	0.52
Match 5	-1.34	-0.85	-0.50	0.50	0.25
Match 6	1.04	-0.90	1.93	1.93	3.74
Match 7	0.29	-0.70	0.99	0.99	0.99
Predicted		-0.60			
Average			0.49	0.98	1.26
RMSE					1.12

Appendix 5.20 Exponential smoothing for Quick Play component - Warrington

	Principal component Score 5	Predicted Score 5	Error	Absolute error	Square error
Match 1	-1.12				
Match 2	-0.25	-1.12	0.87	0.87	0.75
Match 3	0.70	-0.34	1.05	1.05	1.09
Match 4	1.27	0.60	0.67	0.67	0.44
Match 5	2.06	1.20	0.86	0.86	0.74
Match 6	2.40	1.97	0.43	0.43	0.18
Match 7	1.28	2.36	-1.08	1.08	1.16
Predicted		1.39			
Average			0.77	0.77	0.64
RMSE					1.00

Appendix 5.21 Exponential smoothing for Attempt to continue the possession- Warrington

	Principal component Score 6	Predicted Score 6	Error	Absolute error	Square error
Match 1	0.33				
Match 2	-1.20	0.33	-1.53	1.53	2.34
Match 3	1.45	0.18	1.27	1.27	1.61
Match 4	-0.49	0.31	-0.80	0.80	0.64
Match 5	0.09	0.23	-0.14	0.14	0.02
Match 6	-0.98	0.21	-1.19	1.19	1.42
Match 7	0.94	0.09	0.85	0.85	0.72
Predicted		0.18			
Average			-0.26	0.96	1.12
RMSE					1.06

Appendix 5.22 Exponential smoothing for Ratio of penalties gained/conceded component - Warrington

	Principal component Score 7	Predicted Score 7	Error	Absolute error	Square error
Match 1	-0.12				
Match 2	1.65	-0.12	1.78	1.78	3.16
Match 3	-0.55	0.05	-0.61	0.61	0.37
Match 4	0.33	-0.01	0.34	0.34	0.12
Match 5	-0.01	0.03	-0.04	0.04	0.00
Match 6	-1.36	0.02	-1.38	1.38	1.91
Match 7	2.02	-0.11	2.13	2.13	4.56
Predicted		0.10			
Average			0.37	1.05	1.69
RMSE					1.30

Appendix 5.23 Exponential smoothing for Retaining possession following a kick component - Warrington

	Principal component Score 8	Predicted Score 8	Error	Absolute error	Square error
Match 1	-0.52				
Match 2	0.12	-0.52	0.64	0.64	0.41
Match 3	0.76	-0.46	1.22	1.22	1.49
Match 4	-1.84	-0.33	-1.50	1.50	2.25
Match 5	0.07	-0.48	0.56	0.56	0.31
Match 6	0.63	-0.43	1.06	1.06	1.12
Match 7	0.08	-0.32	0.40	0.40	0.16
Predicted		-0.28			
Average			0.40	0.90	0.96
RMSE					0.98

Appendix 5.24 Exponential smoothing Defensive quickness component - Warrington

	Principal component Score 9	Predicted Score 9	Error	Absolute error	Square error
Match 1	0.37				
Match 2	0.46	0.37	0.09	0.09	0.01
Match 3	0.59	0.38	0.21	0.21	0.04
Match 4	0.17	0.40	-0.24	0.24	0.06
Match 5	0.45	0.38	0.07	0.07	0.00
Match 6	0.21	0.39	-0.18	0.18	0.03
Match 7	-1.00	0.37	-1.37	1.37	1.87
Predicted		0.23			
Average			-0.01	0.16	0.03
RMSE					0.17

Appendix 5.25 Exponential smoothing for Player sent off component - Warrington

	Principal component Score 10	Predicted Score 10	Error	Absolute error	Square error
Match 1	0.15				
Match 2	0.23	0.15	0.08	0.08	0.01
Match 3	0.37	0.16	0.21	0.21	0.05
Match 4	-0.84	0.18	-1.02	1.02	1.03
Match 5	-0.10	0.08	-0.18	0.18	0.03
Match 6	0.00	0.06	-0.06	0.06	0.00
Match 7	0.44	0.05	0.39	0.39	0.15
Predicted		0.09			
Average			-0.19	0.31	0.22
RMSE					0.47