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Analysis of Technical & Tactical Performances for Success in the National Rugby League

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The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007). The proposed research methodology received human research ethics approval from the James Cook University Human Research Ethics Committee (approval numbers H7376, H7880 & H7968).

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5. North Queensland Cowboys Rugby League Football Club, Townsville, Australia;
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Nature of Assistance	Contribution *(Specify only those contributions that are applicable to your thesis; the list below is not exhaustive)*	Names, Titles *(if relevant)* and Affiliations of Co-Contributors
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THESIS ABSTRACT

The rapid growth of information technologies has unquestionably changed the landscape of high-performance sport. One such change has been the rise of sports performance analytics as a support discipline in its own right. This has led many professional sporting organisations across the globe to employ performance staff with nuanced skillsets that can help coaching staff sift through quantities of data to find important, actionable insights that have positive implications for on-field success. Indeed, the National Rugby League (NRL) is one such sporting organisation, with many clubs now employing staff members – and even forming departments – that have a primary focus on performance analysis. Though, just how such staff can provide nuanced support to the operations of a professional club within the NRL has yet to be established. This thesis, then, endeavoured to explore the various ways in which performance analysis could support coaching staff with operational decisions relating to technical and tactical aspects of play, at both team and individual scales of analysis.

This thesis contains seven Chapters, of which the first two provide an introduction and review of the surrounding literature. Chapter 3 marks the first of a series of studies that delve into the various technical and tactical contributors to individual and team performance in the NRL. The specific focus of this Chapter was to identify the pre-eminent team playing styles according to season and end of season rank across the 2015-2019 NRL seasons. The main findings revealed nine 'Factors' that accounted for ~51% of season team performance variance, the contribution of which differed from season to season. Generally, successful team playing styles were more reflective of an attacking focus, with a greater emphasis being placed on *play the ball* wins to generate more scoring opportunities.

Chapter 4 extended these findings by examining the effect of various match-related contextual variables on the expression of team playing styles in the NRL. These contextual variables included *match location*, *score-line*, *team quality* and *match outcome*. Discriminant analysis could not meaningfully resolve team playing styles for score-line, team quality or match location. However, one discriminant function was successful in classifying ~81% of matches based on outcome, which included four team playing styles. This led to the conclusion that regardless of match contexts, team success relied heavily upon successful attacking strategies, further corroborating findings from Chapter 3.

Chapter 5 examined the relative contribution(s) and importance of different positional groups to the organisation and success of team playing styles in the NRL over five-seasons. In order to do so, it was important to first understand the profiles of different positional groups and determine their contribution to team performance. Using an unsupervised cluster analysis, six positional groups were ascertained using forty-eight technical performance indicators (PIs). It was noted that these six groups changed significantly over the five-season observational period, demonstrating the dynamic nature of game-play at this elite level.

Utilising the positional groups resolved in the previous chapter, Chapter 6 examined the effects of various match-related contextual factors on team performance. Through decision tree analysis, it was revealed that just three of the six positional groups had a definitive role within the team in explaining match-related contextual factors. Results further revealed that there was a greater emphasis on defensive actions at a positional level relative to variables used to demonstrate attacking actions; a finding that is in direct contrast with team-level research.

Chapter 7 concludes the thesis, summarising its findings and discussing practical implications. Clear applications of the novel analytical techniques used throughout this thesis, such as training drill selection (and manipulation), personnel recruitment and tactical game-planning, are discussed. Further avenues for research are also explored, such as the assimilation of technical, tactical, and physical (spatio-temporal) data for providing a more rounded understanding of total team and individual performance(s).

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LIST OF ABBREVIATIONS

AF	Australian Football
AFL	Australian Football League
ANOVA	Analysis of Variance
CHAID	Chi-Square Automatic Interaction Detector
EPV	Expected Points Value
MANCOVA	Multivariate Analysis of Covariance
nMDS	non-Metric Multidimensional Scaling
NRL	National Rugby League
PCA	Principal Component Analysis
PI	Performance Indicator
PTB	Play the Ball
RL	Rugby League
SC	Structure Coefficient

CHAPTER 1: INTRODUCTION

1.1 Rugby League: a brief history

Rugby League (RL) is a team invasion sport played internationally in over 30 countries. In Australia, the inaugural competition started in 1907 and was played primarily along the eastern coast of the country (Rowe, 1997). Since 1997, the National Rugby League (NRL) has been considered the premier Australasian competition, predominantly hosted in Australia despite the inclusion of a team originating from New Zealand (Rowe, 1997; Sirotic et al., 2009). The NRL currently consists of 16 teams that compete across a 25-round premiership season (Sirotic et al., 2009). Each team is made up of 13 on-field players (with four additional interchange players) that are typically split between two distinct playing groups: forwards and backs (Figure 1). Matches are 80 minutes in duration, split into 40-minute halves – each beginning with one team kicking the ball from the half-way line to the opposing team. Ball possession typically cycles between teams, with each being granted a six-tackle set to attack before possession is forfeited to the opposition. Although, a common tactic used by teams is to 'kick' the ball on their fifth tackle, thereby forcing the opposing team to start their attacking chain of possession as close to their own goal line as possible, or to create an opportunity to score themselves.

Scoring points in RL can be achieved through several means. Tries, however, are the predominant method of scoring, awarding the maximum score (4-points) and affording a team the opportunity to kick for goal, which is worth 2-points – leading to a combined maximum of 6-points. Points can also be scored by making a place kick from a penalty, which is worth 2-points, or successfully converting a drop kick at goal during general play, worth 1-point. Upon scoring, play is restarted by a kick-off, similar to the beginning of each half, with the team that scored receiving the ball back from the kick-off. These rules, which govern the possession and scoring cycles of teams, are also important for dictating the foundation of the tactical organisation (playing style) of teams throughout the time-course of the match (Parmar et al., 2018b; Woods et al., 2018b). An example of this is the recent introduction of the ‘six-again’ rule, brought into the NRL during the 2021 season. This change was intended to increase ‘ball in play’ time by reducing full penalties, thereby providing the attacking team with a restart on their tackle count. However, the unintended side-effects of this change led to a dramatic increase in play the ball (PTB) speeds, with teams looking to exploit slow retreating defensive lines to generate line breaks and further try scoring opportunities.

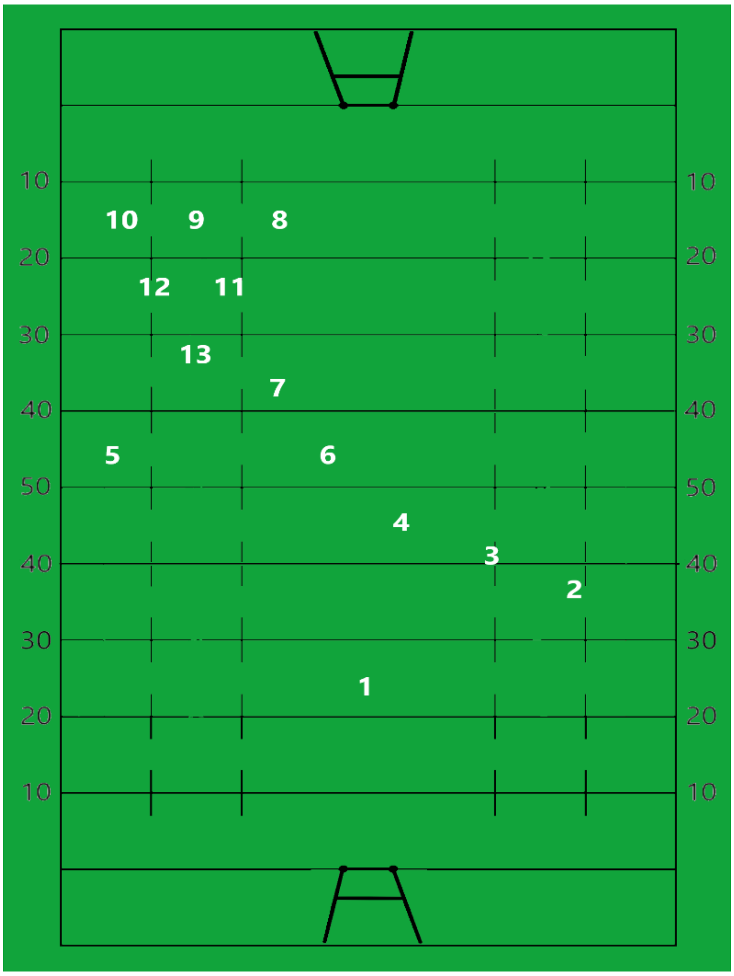

Figure 1. Diagram of Rugby League field with subsequent player numbers and positions (13 – Lock; 12 and 11 – Back Row; 10 and 8 – Front Row; 9 – Hooker; 7 – Scrum Half; 6 – Five Eight; 4 and 3 – Centres; 2 and 5 – Wingers; 1 – Fullback).

To help optimise their chances of scoring and exploiting rules like that discussed above, NRL teams are starting to integrate the role of performance analysts. These specialist sport scientists are typically involved in collecting and analysing technical and tactical performance data. This data comprises of both team and individual information that provides insights to coaching staff about PIs that may be more (or less) important for success (Lord et al., 2020b; Windt et al., 2020). Thus, such information is critical for supporting coaching staff with regards to the design and implementation of training environments, match strategies, and talent recruitment practices. However, given its emerging role in professional sport globally, current and aspiring performance analysts often have to rely on research (and methodology) from other domains to ascertain how they can assist coaching staff with the various day-to-day operations (Li, 2014; Lord et al., 2020b; Windt et al., 2020). It is of note, though, that in RL, research is beginning to explore some of the important technical and tactical PIs that could be important for team success from both a team and individual level, thereby offering an enticing platform for work to come (Parmar et al., 2018a; Sawczuk et al., 2021; Woods et al., 2018c).

1.2 The Role of The Analyst – Supporting Coaching Practices

In professional, high-performance sport, the performance analyst is becoming an increasingly important role (Browne et al., 2021; Windt et al., 2020). This practitioner is typically responsible for gleaning insight into phenomena that governs athlete and team behaviour – such as exploring the effect of match-contexts like location, quality of opposition and score line, on team and individual performance (Gollan et al., 2020). Insights gained can subsequently assist and support coaches with the design of representative practice tasks (i.e., tasks that faithfully represent the contexts and conditions experienced in competition), inform match-strategies, and support player recruitment and retention strategies (Pearce et al., 2020; Pearce et al., 2019; Scott et al., 2021).

Given the rapidly evolving nature of sports technology, the load on performance analysts has increased in recent years, creating more challenges regarding the nuanced skillsets needed to support coaches in making various operational decisions (Houtmeyers et al., 2021; Lord et al., 2020a; Robertson, 2020). Moreover, research from other domains and disciplines (e.g. ecology and computing sciences) has continued to pave a way for analysts to explore the use of various analytical techniques that can be integrated to address questions in practice, albeit notable differences in the phenomena to be explained (Travassos et al., 2017; Woods et al., 2017b). Despite this, performance analytics research – particularly within the NRL – has lagged relative to other professional sports, like basketball (Çene, 2018; Jaime Sampaio et al., 2010; Zhang et al., 2019), soccer (de Jong et al., 2020; Gómez et al., 2018; Lago-Peñas et al., 2018) and Australian Football (Robertson et al., 2016; Woods et al., 2017a; Young et al., 2019). This means that sports performance analysts working within the NRL are at risk of having to extrapolate ideas, concepts, and methods from other sports to expand their own technical expertise. Thus, it would be of interest – given the intentions of this doctoral thesis – to explore some of the research conducted in RL, while discussing how a current or aspiring sports performance analyst could go about expanding their technical repertoire. First, though, I will explore the current landscape of RL literature from both a team and individual (positional) perspective to gain insights into where the current gaps in the literature exist.

1.3 Key Technical and Tactical Characteristics in Rugby League

In each season of the NRL, teams compete for the chance to play in the finals and ultimately attain a premiership. Given this long-term performance goal, it is important that the plans and processes in place that guide training, team selection and playing styles, are constantly evaluated so as to ensure they provide a team with the greatest chance of success

(Parmar et al., 2018b; Woods et al., 2017d). Herein lies a primary role of the performance analyst – the ongoing collection and (re)evaluation of the technical (and tactical) demands that appear to be the most important to win matches and subsequently enable the team to rank high on the ladder (Robertson, 2020; Windt et al., 2020). For example, recent work has examined the technical indicators most important for winning and ranking higher within the NRL (Parmar et al., 2018b; Woods et al., 2018b; Woods et al., 2017d). Notably, Woods et al. (2017d) identified that 'higher performing' (i.e., winning) teams in the NRL performed better in five specific PIs: 'try assists'; 'all run metres'; 'line breaks'; 'dummy half runs'; and 'offloads'. Moreover, the authors identified that 'missed tackles', 'kick metres' and 'offloads' were important in explaining match outcome (Woods et al., 2017d). Such information can offer crucial insight for coaches, not only regarding the PIs that could be monitored throughout a game or season, but it could also encourage coaches to incorporate their experiential knowledge to design practice tasks and game strategies intended to exploit such PIs.

In addition to match outcome, research in the NRL has explored how PIs have evolved over time. Specifically, using 11-seasons of data, Woods et al. (2018b) identified a non-linear evolution of team profiles (i.e., the collective expression of technical skill performance exhibited by the team as an average of individual athletes) in the NRL. This work highlighted that teams tend to 'follow the leader' – trying to emulate how the premiership winning team of that season plays in the following year (Woods et al., 2018). What this suggests, is that teams appear to be purposefully manipulating their playing style to exploit opposition weaknesses and play to the strengths of their own playing roster, whilst observing current trends that exist across the competition. In a similar analysis, Parmar et al. (2018b) identified the technical characteristics that could be grouped in order to highlight important team playing styles in the European Super League. It was noted that when teams placed a greater emphasis on 'amount of possession', 'making quick ground', and 'quick play' with regards to their team playing styles, they were more likely to win (Parmar et al., 2018b). Additionally, Sawczuk et al. (2021) explored expected points value (EPV) of teams' attacking possession in the European Super League – examining the probability of every action-location tuple leading to the scoring of points. They developed two EPV models (EPV-19 and EPV-13) which could provide actionable insights into the attacking performance(s) of teams (Sawczuk et al., 2021). Importantly, the authors suggested that z-score comparisons of opposition EPV scores could generate insights into perceived advantages through different regions of the ground – granting further information for coaches to consider as part of their tactical preparations (Sawczuk et al., 2021). Yet, despite the novel examinations in the English Super League, there is little research within the NRL that has explored the importance of various team playing styles. Further, an exploration of the important team technical and tactical characteristics with regards to team success and additional match-contexts (e.g. match location, quality of opposition, or score line) is lacking when compared to other team sports such as basketball (Gomez et al., 2014; Jaime Sampaio et al., 2010; Zhang et al., 2019), soccer (Gollan et al., 2020; Gómez et al., 2018; Lago-Peñas et al., 2018) and Australian Football (Greenham et al., 2017; Woods et al., 2017a).

Work examining the technical and tactical insights of RL performance at a positional level is also relatively sparse within the NRL. Most empirical work at a positional level has been dedicated to understanding the evolving physical demands of RL players and their subsequent training load (Gabbett, 2004; Masters, 2001), while monitoring fatigue and its impact upon physical output (Coutts et al., 2007; Gabbett & Jenkins, 2011; Mclean et al., 2010). Further, research has identified differences in running, contact and acceleration profiles of different positional groups in RL (Austin & Kelly, 2014; Gabbett et al., 2012; Varley et al., 2014). Whilst the physical positional profiles have been well established, the technical and tactical profiles of these positional groups are yet to be comprehensively examined.

The positional make-up of a RL team could be generally split up amongst four distinct playing groups, each with slightly different physical and technical demands: middle forwards (lock and props); edge back-row; adjustables (halves, hooker and fullback); outside backs (centres and wingers). Given the inherent differences in the responsibilities of each positional group, it would be expected that there would be differences in both the technical and tactical characteristics of different positions in the NRL. Research has identified PIs capable of differentiating playing position (backs, forwards, fullback, Hooker, and service players) in RL (Sirotic et al., 2011). The authors identified that forwards, hookers, and service players (halfbacks and five-eight players) completed more tackles per minute than both backs and fullbacks, whereas both backs and fullbacks completed more runs with the ball than all other positional groups (Sirotic et al., 2011). Moreover, Bennett et al. (2016) compared the total number of offensive and defensive actions performed by three different positional groups (forwards, backs, and adjustables) amongst junior RL players. It was observed that forwards (props, lock, and back rowers) completed the greatest number of both offensive and defensive actions compared to adjustables and backs, while adjustables completed a significantly greater number of defensive and total technical skills compared to the backs (Bennett et al., 2016). Whilst limited, the results of these studies show that players' game involvements are likely to vary according to playing position. In fact, some have suggested that the relative success of RL teams may depend more on technical and tactical differences in performance between players, rather than physical performance (Hulin et al., 2015; Kempton et al., 2017); sentiments noted in other football codes (McIntosh et al., 2018; Rampinini et al., 2009; Sullivan et al., 2014). Indeed, while research can be extrapolated across sports, nuances of the game may be over- or under-estimated, leading to misguided practices. Thus, in order to create a greater platform for analysts and coaches working within the NRL – thereby helping them resolve specific technical and tactical indicators from both individual and team perspectives – additional research is needed.

1.5 Research Aims

The primary aim of this doctoral thesis was to explore how the use of various analytical techniques could resolve team and positional performance characteristics explanatory of success in the NRL. To address this, four research aims were developed:

1. To identify the dominant team playing styles in the NRL that are important for ranking high on the ladder.
2. To examine the effect of differing match-contexts on the expression of team playing styles in the NRL over recent seasons.
3. To identify technical performance characteristics important for differentiating positional groups in the NRL.
4. To explore the effect of differing match-contexts on the expression of positional technical performance(s) and the subsequent influence collective team performance.

1.6 Thesis Overview

This thesis consists of seven chapters, of which the first has provided a brief introduction to RL and its premier competition within the southern hemisphere, the NRL. Chapter 2 provides a narrative literature review, which introduces the use of novel analytical techniques for the examination of technical and tactical performance(s) in high-performance sport, with a primary focus on RL. The narrative review serves to identify current gaps and limitations of existing research, further explored through the novel addition of case examples that aim to provide the foundation of the following research chapters (Chapters 3 – 6). Chapter 7 provides a summary of the doctoral thesis, with concluding statements regarding the practicality of this research, and its areas for future exploration.

CHAPTER 2: Operational Insights into Analysing Team and Player Performance in Elite Rugby League: A Narrative Review with Case Examples

Publication

Wedding, C.J., Woods C.T., Sinclair W.H., Leicht A.S. (Under Review). Operational Insights into Analysing Team and Player Performance in Elite Rugby League: A Narrative Review with Case Examples. Sports Medicine Open.

Author Contributions

C.J.W. contributed 75% to this chapter. He developed the chapter structure, wrote each section, collated and analysed the data. C.T.W offered conceptual guidance and support (15%), while both A.S.L and W.H.S contributed to the manuscript drafting and construction of ideas within the discussion (10%).

2.1 Abstract

In professional team sports, like Rugby League, performance analysis has become an integral part of operational practices. This has helped practitioners gain deeper insight into phenomenon like team and athlete behaviour and understanding how such behaviour may be influenced by various contextual factors. This information can then be used by coaches to design representative practice tasks, inform game principles and strategies, and even support team recruitment practices. At the elite level, the constant evolution of sports technology (both hard- and software) has enabled greater access to information, making the role of the performance analyst even more valuable. However, this increase in information can create challenges regarding which variables to use to help guide decision-making, and how to present it in ways that can be utilised by coaches and other support staff. While there are published works exploring aspects of performance analysis in team sports like Rugby League, there is yet to be a perspective that explores the various operational uses of performance analysis in Rugby League. The addition of which could help guide the practices of emerging performance analysts in elite organisations like the National Rugby League. Thus, this narrative review – with accompanying case examples – explores the various ways performance analysis can help address pertinent operational questions commonly encountered when working in high-performance sport.

2.1 Introduction

Sports performance analysis is an increasingly important part of operational practices in high-performance sport (Browne et al., 2021; James, 2006; Windt et al., 2020). So much so, that many professional organisations now staff positions with full-time specialists and at times, form entire departments – roles which are supported by the growing tertiary offerings of postgraduate degrees in sports performance analytics. Despite the nuance of these positions, the role of the performance analyst in high-performance sport is often diverse, assisting practitioners with questions stemming from practice task design (Yi et al., 2020; Zhang et al., 2018), team strategies in competition (i.e., the development and monitoring of game principles) (Almeida et al., 2014; Ariff et al., 2015; Parmar et al., 2018a; Robertson et al., 2016), team selection and recruitment (Till & Baker, 2020; Woods et al., 2016; Woods et al., 2017e), and the efficacy of long-term performance gains associated with various training interventions (Browne et al., 2020; Pol et al., 2020). Such operational insights can also span multiple developmental levels (i.e., junior-to-senior transition), offering insight into individual, team or competition-wide behaviours that change over varying timescales (i.e., within or across a season(s)) (Goes et al., 2020; Lord et al., 2020b).

There is, however, a trade-off associated with this growing operationalism of performance analysis in high-performance sport. Notably, there is an increased strain on support staff to analyse and present data in meaningful and actionable ways for coaches, athletes and other support staff (Goes et al., 2020; Robertson, 2020; Windt et al., 2020). Magnifying this challenge, there is little empirical guidance that supports performance analysts working in high-performance sport when navigating the varying methods available for the analysis of the ever-growing sea of data, fuelled by the rise of sports technology (Haake, 2012). This, in part, could be due to the diverse questions and problems that performance analysts in high-performance sport are often asked to assist with – demanding a range of adaptable skillsets (Robertson, 2020). Whilst the introduction of various graduate courses and certificates in sports performance analytics at tertiary institutions have begun to support the next wave of performance analysts[1], there is little information available for those already working within professional sport.

In light of this, the current narrative review aims to present a sample of techniques that could be of use for developing performance analysts, primarily focused on the team sport of Rugby League. This review does not intend to cover an exhaustive set of analytical techniques, but rather focuses on certain ones that could be of assistance to developing performance analysts in Rugby League, associated with common questions asked by coaches at varying levels of competition. The review is set out in two parts – the first reviews techniques related to data reduction and clustering, decision trees, and logistic regression. In the second, three case examples that demonstrate each technique in practice are presented. The goal of this second part is to act as a means of demonstration, guiding developing performance analysts in how they may employ such techniques, rooted in real-world questions. Thus, the questions posed in these case examples are questions in which the first author of this paper, who is currently working as a performance analyst at a professional Rugby League team, has had to navigate. So, what is 'out there' for developing sports performance analysts interested in individual and team performance in high-performance sport?

[1] University, V. Graduate Certificate in Data Analytics for Sport Performance. 2021; Available from: https://www.vu.edu.au/courses/graduate-certificate-in-data-analytics-for-sport-performance-stsp; London, M.U. Sport Performance Analysis MSc/PG Dip/PG Cert. Available from: https://www.mdx.ac.uk/courses/postgraduate/sport-performance-analysis; University, D. Graduate Certificate of Sport Performance Analysis. 2021; Available from: https://www.deakin.edu.au/course/graduate-certificate-sport-performance-analysis?_ga=2.60891180.1647635532.1626061200-1666776876.1623797527&_gac=1.21229257.1626061200.CjwKCAjwn6GGBhADEiwAruUcKoSqIcKSsOXrm08ON1SF4UTBCV57kpJeYdu34OQYdMkiJm9LFYo46xoCuq4QAvD_BwE.

2.2 Part 1 – Overview of key techniques for sports performance analysts

Performance Analysis Practices in Team Sports

Like any high-performance environment, successful performance in elite-level sport requires skilled functionality, such as working out ways to offload the ball in Rugby League (Wheeler et al., 2011), or ways of serving to various regions of a tennis court to exploit opponent positioning (Cui et al., 2019). These sports-specific functional components are often referred to as 'technical skills' (Hughes & Bartlett, 2002), and are typically captured by performance analysts to help coaches understand various aspects of game-play as it unfolds. For example, capturing and analysing information related to how a player obtains and then disposes of the ball (via a kick or handball) in Australian football (AF) can assist coaches with the design of training activities intended to promote the development of offensive behaviour (Browne et al., 2020; Piggott et al., 2019). Further, application of similar notational analyses at a team-level could lead to information that resolves team behaviour – manifest in styles or common patterns of play – which can be modelled relative to outcomes like match success. For example, Lago-Peñas et al. (2018) identified five Factors (i.e., groups of PIs) that explained various styles of play across an elite soccer competition, information which they argued could be strategically used by coaches to counter an opposition. As I now go onto discuss, an integral component of the analysis used by Lago-Peñas et al. (2018) was data reduction and clustering – whereby large multidimensional datasets were reduced to Factors and clustered based on their similarity, allowing practitioners to make decisions with reference to a select few (important) variables (Gómez et al., 2018; Parmar et al., 2018a; Woods et al., 2018b).

2.2.1 Data Reduction and Clustering

While sports technology has unquestionably assisted performance analysts (Browne et al., 2021), it has resulted in a large quantity of data to be filtered, analysed and reported in actionable ways (Lord et al., 2020b; Rojas-Valverde et al., 2020). This has likely led to uncertainty with regards to variable selection – defined as which variables (or groups of variables) are important in supporting practitioners in making decisions guided by sports performance data (Lord et al., 2020b; Travassos et al., 2017). In light of this, performance analysts have sought to apply various data reduction techniques – common to other quantitative disciplines (Faith et al., 1987; Pedelty et al., 1985; Travassos et al., 2017) – to hone in on (combinations of) PIs most important for explaining an outcome of interest (Goes et al., 2020; Lord et al., 2020b; Rein & Memmert, 2016). In its broadest sense, data reduction is a process by which large – often multidimensional – datasets can be reduced into smaller, more manageable sets, while ensuring the integrity of the data is not compromised (Rojas-Valverde et al., 2020). In high-performance sport where the quantity of data is expanding given the automation of various sports technologies, such reduction techniques can be important.

While there are a variety of data reduction techniques, two of the more common seen in team sports like Rugby League are *principal component analysis*, and *multidimensional scaling* (Chapter 5; Parmar et al., 2018b; Woods et al., 2018b). Both principal component analysis and multidimensional scaling produce a series of *Factors* which represent groups of similar variables (Jolliffe, 2011; Weaving et al., 2019; Woods et al., 2017b). However, these techniques differ with respect to the processes involved with the creation of these Factors. For example, principal component analysis resolves linear, uncorrelated sets of variable combinations – achieved by resolving the eigenvalue; a scaling factor which determines the magnitude and number of principal components (Factors) to be used (Jolliffe, 2011; Rojas-

Valverde et al., 2020; Weaving et al., 2018). Whilst multidimensional scaling relies on non-parametric regression to determine a dissimilarity ranking matrix to produce a series of dimensions, iteratively searching for least squares fit based on the rank-order of the dissimilarities (Woods et al., 2017b; Woods et al., 2018b; Zhang et al., 2019). The rank-order of dissimilarities and subsequent Factors obtained via principal component analysis can then be used to explain various aspects of performance, such as what PIs are important for winning a match of Rugby League (Chapter 3; Parmar et al., 2018a; Parmar et al., 2018b;). But how (or why) might we choose to use one technique over another? The key characteristics in each of these analyses are important to consider prior to selecting and utilising one over the other. For example, as principal component analysis assumes a linear relationship within the data and the latent variables represented as Factors, applying this technique to a non-linear dataset may struggle to appropriately represent the distance measures between Factors. Multidimensional scaling, on the other hand, assumes no linearity and strives only to optimise the fit between the dissimilarity of objects and the rank-order of dissimilarities. Thus, understanding dataset properties is an important initial step in determining which technique is most appropriate in reducing its multidimensionality for sports performance analysts.

The use of these data reduction techniques has grown within Rugby League research. For example, Woods et al. (2018b) highlighted the utility of multidimensional scaling for explaining the evolution of game play within the National Rugby League over an 11-year period. These authors reduced a multidimensional dataset, visualising the ranked dissimilarities to show how the game has evolved in a 'follow-the-leader' type manner, postulating how coaches could use such insights to develop innovative styles or principles of play 'beyond their time'. Comparatively, Parmar et al. (2018a) highlighted the utility of principal component analysis for the analysis of team performance in the European Super League. These authors identified that 'making quick ground', 'quick play' and 'amount of possession' were the most important Factors for explaining match outcome (Parmar et al., 2018a). Similarly, Wedding et al. (2021a) explored the use of principal component analysis for team performance analysis in the National Rugby League, identifying nine Factors (six attacking, two defensive and one contested) which could explain team playing styles relative to season and end of season rank – uncovering important characteristics for consideration in the design and implementation of game planning. Research in other sports such as soccer (Gómez et al., 2018; Lago-Peñas et al., 2018), basketball (Jaime Sampaio et al., 2010; Zhang et al., 2019) and AF (Woods et al., 2017a) have further exemplified the use of principal component and multidimensional scaling in identifying the performance characteristics most explanatory of team performance variance and playing style over varying time periods. Each of these studies demonstrates the value of data reduction in making actionably smaller subsets of data that maintains its underlying integrity. A further example of the utility of such a technique for servicing operational practices in Rugby League can be seen in the first Case Example, discussed in the second part of this review.

Clustering is another data reduction technique that is growing in popularity in sports performance analytics (Mukherjee et al., 2018; Sampaio et al., 2018). A specific clustering technique discussed here is *two-step clustering* – a technique which reveals 'natural' clusters (or groupings) within a dataset using log-likelihood distance measures (Chapter 4; Mukherjee et al., 2018; Zhang et al., 2018). The utility of clustering for explaining phenomena in sport, like match outcome, has been exemplified by Gomez et al. (2014) who grouped the performance of wheelchair basketball teams based on different match types (defined through score-lines of 'unbalanced' or 'balanced'). In being able to successfully cluster teams according to score-lines, these authors demonstrated the use of this technique for reducing and visualising data into meaningful groups, which they argued was information important in supporting coaches to design game and practice strategies (Gomez et al., 2014). Further, Zhang et al. (2018) utilised two-step clustering to identify five different player profiles of professional basketballers using anthropomorphic, technical and physical variables – thereby supporting recruitment and talent selection. As an important aside, this study demonstrated the use of two-step clustering for handling data of variable properties (i.e., categorical and continuous), which is particularly critical for high-performance sport given the diverse sources of data often available to performance analysts (Mukherjee et al., 2018; Whitehead et al., 2020). The use of two-step clustering for examining positional performance in Rugby League has been exemplified by Wedding et al. (2020), who successfully identified six positional groups (as compared to four *a priori*) – enabling the establishment of player performance profiles for performance assessment, player development and recruitment strategies.

Whilst only a snapshot of the available work, these studies highlight the benefit of various data reduction and clustering techniques for sports performance analysts in high-performance environments. Nonetheless, to further guide developing performance analysts in adopting these data reduction techniques, the second part of this narrative review weaves in a case example demonstrating their use in practice. Before this, however, I will explore the use of *decision support analysis* (specifically decision trees) for sports performance analysts – showing how such a technique can support coaches and other practitioners in understanding the (non-linear) interaction between variables, and how these interactions relate with various outcomes of applied practical interest.

2.2.2 Decision Support Analysis

Indeed, data reduction and clustering analyses are some of many increasingly adopted methods for understanding what ‘successful’ or winning performances look like in high-performance sport (Gómez et al., 2018; Parmar et al., 2018a; Zhang et al., 2018). However, to support coaches in modifying targeted features of a game style to increase the probability of attaining a successful outcome, *decision support analyses* can be useful. Broadly, decision support analysis can support a practitioner by sifting through large quantities of data to identify underlying interactions and their conditional control statements, with this information being used to ascertain the probabilities of certain outcomes occurring (Bunker & Thabtah, 2019; Robertson, 2020; Robertson et al., 2017). The probabilities of these outcomes occurring can be visually represented in various forms – which can be easily interpreted and presented to coaching staff (Joash Fernandes et al., 2020; Parmar et al., 2018b) – guiding, challenging, or informing decision making (de Jong et al., 2020; Parmar et al., 2018b).

A growing decision support analysis in sports performance analytics are decision trees (Lord et al., 2020b; Maneiro et al., 2019; Yildiz, 2021). As the name implies, decision trees are models of decisions grown from a root or parent node, which iteratively grow branches that visualise the interaction between key variables and their conditional statements, explaining the probability of a certain outcome (Maneiro et al., 2019). There are two primary types of decision trees: classification and regression (Biggs et al., 1991; Breiman, 2001; Rokach & Maimon, 2005). Whilst there are some similarities between them (namely, that neither require data normalisation), there are some key differences related to how the data is differentiated, grown or split during the analysis (Biggs et al., 1991; Rokach & Maimon, 2005). Specifically, these differences relate to the underlying growth algorithm of the tree (Biggs et al., 1991; Breiman, 2001; Rokach & Maimon, 2005), meaning that while decision trees can be a useful tool for analysts given their capability to visualise complex, non-linear interactions between variables, it is important to understand the appropriateness of types based upon the question asked and data used to grow the model (Biggs et al., 1991; Maneiro et al., 2019). For example, if wanting to explain a binary variable of interest (i.e., win or loss / home or away), a CART (classification and regression tree) method may be appropriate. Joash Fernandes et al. (2020) exemplified the use of CART as a method for explaining the likelihood of a passing or rushing play occurring at any point during a National Football League game. On the other hand, if seeking to explain a non-binary outcome, a CHAID (chi-squared automatic interaction detection) algorithm may be appropriate given that it utilises multi-way splits, which could be used to identify multiple styles or phases of play (Parmar et al., 2018b). Not only are the number of splits that may occur from any given node different depending on which model chosen, but so too is the way in which the model decides how to make these splits and when it decides to stop splitting (Biggs et al., 1991; Breiman, 2001; Maneiro et al., 2019). Thus, understanding which tree to use is an important initial step for sports performance analysts – being implicated by the question seeking to be answered and the data used to answer it.

In team sports, decision trees have shown capability to explain complex interactions of PIs that contribute to match outcome in AF (Robertson et al., 2016; Young et al., 2019), Rugby League (Parmar et al., 2018b; Whitehead et al., 2020; Woods et al., 2017c), basketball (Çene, 2018; Leicht et al., 2017), and soccer (de Jong et al., 2020). Further, decision trees have been used to identify performance gaps between competition levels, with such information being critical to support decision making regarding talent development in sports like Rugby League (Pearce et al., 2020; Pearce et al., 2019; Woods et al., 2017c). Beyond team performance, decision support analysis has been used to explain player and playing position behaviours within team sports (Sampaio et al., 2018; Woods et al., 2018c; Zhang et al., 2018). Morgan et al. (2013), for example, highlighted that attackers held a distinct advantage in one-on-one situations in hockey when attackers were moving at velocities $\geq 0.5 m.s^{-1}$, resolved using decision tree analysis. However, in instances where the initial speed differential between attackers and defenders was small (<$0.5m.s^{-1}$), the attackers probability of winning the encounter could improve if defenders held a lateral speed >$1.4m.s^{-1}$ (Morgan et al., 2013). This level of detail clearly supports practitioners and athletes in the design of practice tasks and establishment of various strategies intended to exploit opponents and gain a competitive advantage. Thus, decision support analyses, like decision trees, have proven useful in high-performance sport, particularly regarding the identification of team PIs and their conditional control statements that lead to increased chances of attaining match success (Çene, 2018; de Jong et al., 2020; Robertson et al., 2016).

Successful application of these techniques could offer practitioners another way of analysing and visualising some of the various interactions that may occur during a match – further supporting decisions around training and game-planning strategies. The case examples detailed in the second part of this review exemplify the practical utility of decision support analysis for the resolution of important team playing styles for playing at home or away within Rugby League. Prior to this, though, I will explore the use of *logistic regression* for sports performance analysts – highlighting how this technique could be implemented as another method to support coaches and other support staff in understanding the various interactions that may exist within the various training and match data.

2.2.3 Logistic Regression

So far, this review has examined the efficacy of data reduction, clustering and decision support analysis for the exploration of important technical and tactical characteristics in high-performance sport. Logistic regression is a technique used to exclusively model the probability of a dichotomous event (e.g. win or loss) occurring whilst accounting for one or more independent variables that influence the event (Leicht et al., 2017; Parmar et al., 2018a; Peng et al., 2002). There are many benefits of implementing this analytical technique, one being that it is able to provide magnitude (both size and direction) of the relationship for each of the given independent variables modelled (Peng et al., 2002). Further, logistic regression has the ability to handle both continuous (e.g. height, speed, time) and categorical (e.g. win or loss and home or away) independent variables, enabling the integration of larger, diverse datasets, which is common to elite level sport (Peng et al., 2002). However, like many of the other methods described in this review, it does require nuanced interpretative understanding. Additionally, logistic regression models are preferable to use with large(r) datasets, as this reduces the likelihood of modelling error through overfitting as a result of not enough data (Peng et al., 2002). In saying this, given the vast amount of data available within sport, it is unlikely that this would be an issue for most practitioners (Peng et al., 2002).

Demonstrating its utility in high-performance sport, Gollan et al. (2020) modelled the interactions between different playing styles and match-contexts (match location, opposition quality and combined effects of both) in the English Premier League. The authors identified that irrespective of match location (home or away), teams were more likely to demonstrate an established offence and set pieces when they encountered weaker opposition (Gollan et al., 2020). Conversely, weaker opposition were less likely to play this same style when competing against their stronger counterparts – emphasising the importance of understanding the tendencies of opposing teams, such that effective game-plans can be designed to counter them (Gollan et al., 2020). Similarly, Parmar et al. (2018a) highlighted the ability of logistic regression in modelling the probability of team success within Rugby League using PIs clustered via principal component analysis. Their results highlighted a 91% probability that a team would win if able to outperform their opponent in a series of grouped PIs. Practically, presenting such information to coaches could support the development of match strategies that attempt to exploit the styles of play most likely leading to a win. Interestingly, logistic regression has also been used to guide training planning and periodisation by modelling the difficulty of teams' playing schedule across the course of a competitive season in rugby union (Robertson & Joyce, 2018; Robertson & Joyce, 2015). While Woods et al. (2015) demonstrated its utility for talent identification in junior AF – modelling the relationship between performance in various skill tests and team association. Thus, collectively, work such as this demonstrates the diverse use of logistic regression in the sports performance analysis literature – ranging from modelling styles of play, supporting the planning and periodisation of practice, to assisting with talent identification. While in different sports, each of these themes are important in professional Rugby League and are topics that a developing sports performance analyst can assist with.

In reference to the abovementioned, the next section of this narrative review seeks to exemplify each of these techniques, applied to key questions in Rugby League that the first author has had to navigate as a professional sports performance analyst. Thus, it is hoped that these examples can offer aspiring and developing performance analysts working in Rugby League (or other sports) with guidance when seeking to take up with similar questions and analyses.

2.3 Part 2 – Case Examples

2.3.1 Case Study 1: Are there identifiable playing styles in the NRL and are these implicated in playing away or at home?

2.3.1.2 Introduction

The growth of systems thinking within team sport has increased levels of interest regarding the examination of collective behaviours and playing styles (Ribeiro et al., 2019). Broadly speaking, playing style, in team sports like Rugby League, can be defined as an identified way of playing in different phases of the game (i.e., attack, defence or transition) (Fernandez-Navarro et al., 2016; Gómez et al., 2018; Lago-Peñas et al., 2018). These styles of play are considered to be deliberate tactical patterns exhibited by teams while attacking, defending or when attempting to regain ball possession (Gómez et al., 2018). Importantly, research has identified methods for resolving these playing styles using match technical PIs (Fernandez-Navarro et al., 2016; Lago-Peñas et al., 2018; Parmar et al., 2018a). However, these playing styles are often governed by highly complex, non-linear interactions between players and their environment, and thus linear approaches to analysis may not suffice. Accordingly, implementing the use of analytical techniques, like those described in the first part of this paper, could be useful in resolving game styles in team sports.

In this case study, I have exemplified the utility of data reduction and decision support analysis – manifest through the use of principal component analysis, logistic regression modelling and exhaustive CHAID decision trees – for the identification of team playing styles, and their subsequent importance for explaining match success in the NRL. Further, I will show the impact of factors, such as match location, on the identified playing styles.

2.3.1.2 Methodology

Data was collected from the first 10 rounds of the 2021 NRL season. The data chosen included a selection of 25 technical PIs from full matches and both competing teams, in accordance with previous work (Parmar et al., 2018a; Weaving et al., 2019). The data used in this example have been provided as a supplementary file for readers and any additional data can be found on the following commercial website (www.nrl.com/stats/).

To identify playing styles across the sample used, principal component analysis was used to reduce the total dataset into Factors. As discussed in part one of this paper, these Factors have been used to identify key playing styles of teams within soccer (Fernandez-Navarro et al., 2016; Gómez et al., 2018; Lago-Peñas et al., 2018) and the European Super League (Rugby League) (Parmar et al., 2018a; Parmar et al., 2018b). Thus, for the purpose of this example and like has been done elsewhere, the Factors resolved here are intended to represent 'styles of play'.

Logistic regression was then used to determine which Factors were most explanatory of winning (and losing) in the NRL (Parmar et al., 2018a; Peng et al., 2002). Exhaustive CHAID was used to identify how match outcome effected team performance, using match location and the previously identified Factors (playing styles) (Cui et al., 2019). Match outcome was the dependent variable, with the first split forced for match location (home or away) to enable subsequent CHAID results to clarify how winning and losing could be explained by match location. All statistical analyses were carried out using the statistical software IBM SPSS for Windows version 25 (Armonk, NY, USA, IBM Corp.).

2.3.1.3 Results

The results of the principal component analysis identified six Factors, accounting for 74.6% of the total team performance variance across the first 10 rounds of the 2021 NRL season. In order to determine which PIs helped resolve which Factor(s), values greater than 0.60 were extracted from the rotated component matrix (Table 1).

Table 1. Identified playing styles (Factors) with their associated technical performance characteristics.

Style	PIs making up this style
'Scoring'	*Points For, Points Against, Points Differential, Tries, Try Assists, Run Metres, Linebreaks;*
'Attacking Play'	*Hit Ups, Passes, Runs, Tackled inside opposition 20m;*
'Kick Returns'	*Kick Return and Kick Return Metres;*
'Kicking'	*Kicks, Kick Metres, Errors*
'Offloads'	*Offloads*
'Dummy Half Runs'	*Dummy Half Runs*

The logistic regression model explained 91.7% (Nagelkerke R^2) of the variance of match outcome and was able to correctly classify 96.3% of all matches according to outcome. The model identified that teams were twice as likely to win when playing at home when compared to playing away (Exp(B) = 2.053). The exhaustive CHAID model was able to accurately classify match outcome 88.8% of the time using just match location and one identified style: 'Scoring'. The visual representation of the CHAID model is presented in Figure 2, showing that the first split of the parent Node (Node 0) was done using match location; Node 1 (Home) and Node 2 (Away). Node 1 was split by 'Scoring', whereby teams had a 94.7% chance of winning at home when they produced >0.17 of the 'Scoring' component score (Node 4). Conversely teams' likelihood of winning dropped to 15% (Node 3) when producing ≤0.17 component score for 'Scoring'. When playing away from home, teams that produced a component score for 'Scoring' >-0.068 had a likelihood of winning at 86.8% (Node 6), compared with teams that had a component score ≤-0.068, which had an 11.4% likelihood of winning (Node 5).

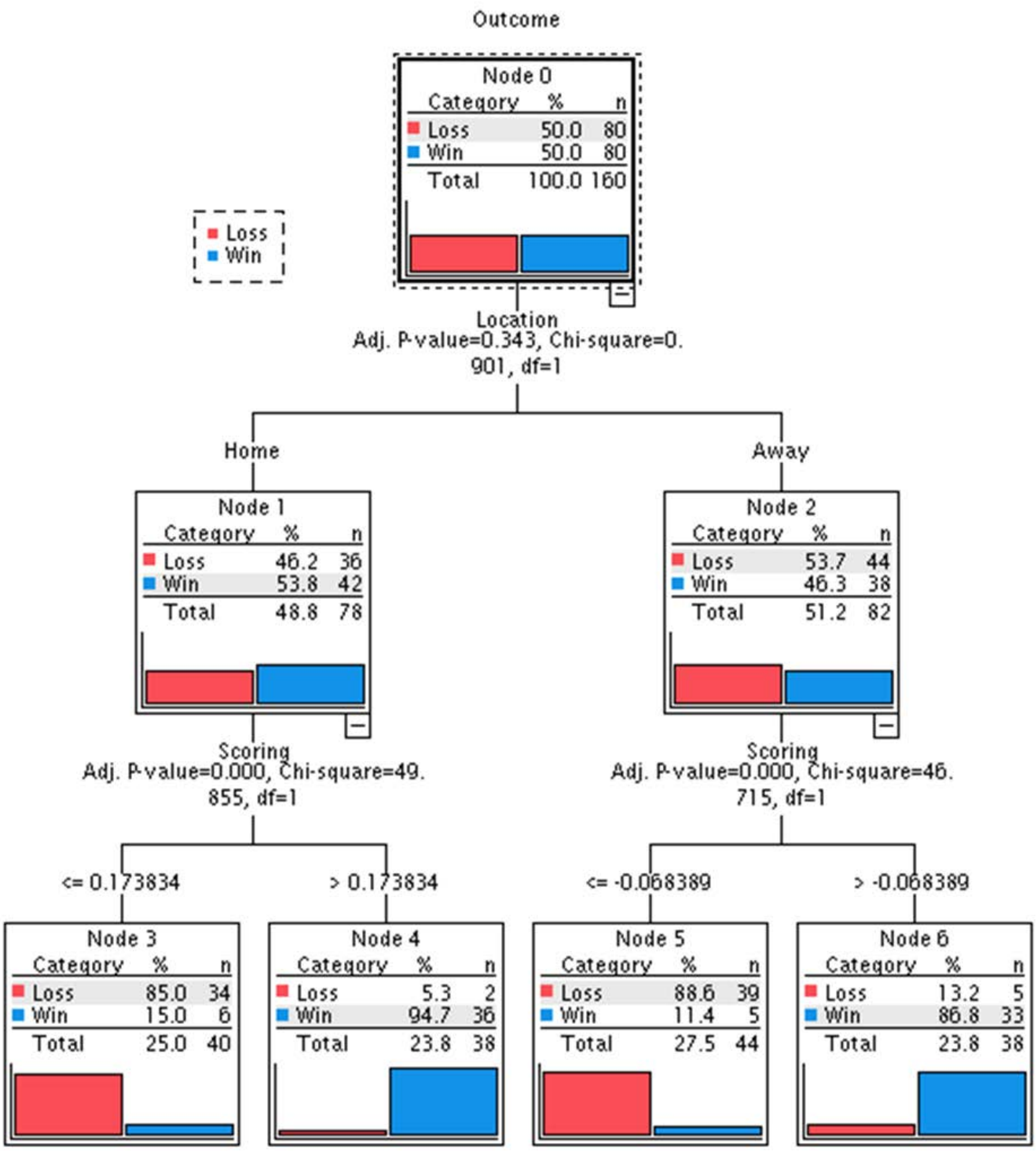

Figure 2. Exhaustive CHAID model of match outcome as influenced match location and team PIs.

2.3.1.4 Conclusions and Practical Implications

The aim of this case study was to exemplify for sports performance analysts a way in which they could identify playing styles in Rugby League, and how to then model these styles against outcomes like playing at or away from home. This was done using principal component analysis, logistic regression and decision tree modelling, each discussed in part one of this narrative review. The principal component analysis revealed six Factors, which were used as proxies of playing style, with 'Scoring', 'Attacking Play' and 'Kick Returns' appearing most prominent over our sample period. The groups of PIs that made up these styles are seemingly important for distinguishing between successful and unsuccessful match performance in the NRL. Further examination of the results from the logistic regression and exhaustive CHAID models showed that both were able to correctly classify match outcome when playing at home (or away) using various playing styles >85% of the time. These results highlight a good level of classification accuracy for both models, demonstrating the utility of either model for the identification of playing styles important for match success in the NRL. Thus, the use of analyses like those in this example can be taken by sports performance analysts to support coaches in the design of training and competition strategies that could exploit current, seemingly advantageous styles of play.

2.3.2 Case Study 2: Can we use match data to model different positional groups using data reduction and classification techniques?

2.3.2.1 Introduction

In addition to team performance, it is important to consider the varying contributions (or interactions) that may be present across the playing group (as individuals). It is these interactions, or the capabilities of playing personnel, which can be an important component of how a team performs. For example, research in AF (Greenham et al., 2017; Woods et al., 2018c; Woods et al., 2017e), basketball (Jaime Sampaio et al., 2010; Zhang et al., 2017; Zhang et al., 2018) and soccer (Aguado-Méndez et al., 2020; Bush et al., 2015) has identified various PIs that differentiate playing positions – information which can support the design and implementation of positional training and match strategies. So, how might a sports performance analyst in Rugby League identify unique playing position characteristics, used as a basis to inform operational practices like training task design or talent recruitment?

2.3.2.2 Methods

Like in the first case study, data was collected from the first 10 rounds of the 2021 NRL season. This included data for each individual for each match, which was then made relative to time played (per 80 minutes). All players positions were categorised *a priori* according to their listed playing position (player number) for that match; forward, back, spine (halves, hooker, fullback) and interchange (Chapter 5). The data used in this example have been provided as a supplementary file for readers (appendix 2) and any additional data can be found on the following commercial website (www.nrl.com/stats/).

To allow for the automatic resolution of playing positions, the dataset was first reduced into Factors using principal component analysis (Jolliffe, 2011; Rojas-Valverde et al., 2020), with an eigenvalue of >1 (Rojas-Valverde et al., 2020). Following this, two-step cluster analysis was utilised to determine the optimal number of positional groups (clusters) through the use of the Schwartz's Bayesian Information Criterion (Norusis, 2011; Wendler & Gröttrup, 2016). The 'goodness' of the clustering was resolved by the silhouette coefficient, and additional log-likelihood distance measures were used to calculate the similarity between clusters (Norusis, 2011; Wendler & Gröttrup, 2016). All statistical analyses were carried out using the statistical software IBM SPSS for Windows version 25 (Armonk, NY, USA, IBM Corp.).

2.3.2.3 Results

The results of the principal component analysis identified seven Factors, accounting for 76.1% of the individual performance variance across the first 10 rounds of the 2021 NRL season. In order to determine which PIs resolved which Factor(s), values greater than 0.60 were extracted from the rotated component matrix (Table 2).

Table 2. Resolved Factors and their associated technical performance characteristics.

Factor	PIs making up this Factor
Factor 1 'Attacking'	*Tries, Runs, Run metres, Linebreaks, Tackle Busts, Tackled in opposition 20m, Tackles made;*
Factor 2 'Kicking'	*Kicks, Kick Metres;*
Factor 3 'Kick Returns'	*Kick Return and Kick Return Metres;*
Factor 4 'Defensive Negatives'	*Minutes played (-), Metres after contact conceded, offloads conceded;*
Factor 5 'Errors'	*Errors, Missed Tackles;*
Factor 6 'Dummy Half Passing'	*Dummy Half Runs, Passes;*
Factor 7 'Offloads'	*Offloads*

Two-step cluster analysis achieved a good silhouette measure of cohesion and separation (average silhouette = 0.7), revealing five positional classifications (clusters) in comparison to the four *a priori* positional groups. These positional classifications were:

- ***Cluster 1 ('Spine'):*** 99.7% classification accuracy, 21.3% of all players
- ***Cluster 2 ('Utility'):*** 3.6% of all players, group splits as follows, 49% adjustables, 25% interchange, rest split between forwards and backs.
- ***Cluster 3 ('Interchange'):*** 100% classification accuracy, 24.5% of all players
- ***Cluster 4 ('Forward'):*** 100% classification accuracy, 28.2% of all players
- ***Cluster 5 ('Back'):*** 99.8% classification accuracy, 22.4% of all players

2.4.4.4 Conclusions & Practical Implications

The aim of this case study was to exemplify a way in which developing sports performance analysts could identify various characteristics important for different playing positions in the NRL. This was achieved using a combination of analytical methods discussed in the first section of this paper; namely, principal component analysis and two-step clustering. Two-step cluster analysis revealed a fifth positional group not originally classified, identifying the positional group which could be classed as a 'Utility' player. This could be important information for coaches when making decisions around player recruitment and match-day interchange rotations. However, in order to determine the influence of each positional group on overall team success, further investigation would be required, possibly using some of the other approaches used in the first case study. Nevertheless, the use of analyses presented in this case study demonstrate the benefit in combining both clustering and classification approaches when seeking to understand the characteristics of different positional groups in the NRL. Further, these approaches could be used to support performance analysts with their evaluation of player performance and future positional suitability with regards to talent identification, personnel recruitment and roster management.

2.5 Conclusions

The growth and continued integration of sports technology can be both a blessing and a curse. For the former, it can automate the collection of data which would otherwise be laborious, yet for the latter, it can create large amounts of data that can be difficult to extract meaning from. Thus, it is important for developing performance analysts working in high-performance sport to learn *when*, *why* and *how* to utilise various analyses to support coaches in their decision making. Thus, this narrative review sought to discuss some key techniques of data reduction, clustering, decision support and logistic regression that could be taken up by performance analysts in the field. Following which, it sought to exemplify how such techniques could be used by sports performance analysts working in professional Rugby League.

Indeed, this narrative review was not exhaustive, nor did it intend to be. It aimed, specifically, at introducing various techniques, exemplifying their use in Rugby League – thereby offering a basis from which developing performance analysts could begin to explore. It is envisaged that future research will follow on from the examples presented here – offering a more comprehensive insight into how techniques of data reduction, decision support analysis and logistic regression modelling can guide various operational practices in high-performance sport.

2.6 Key Points

- Data reduction and clustering, logistic regression and decision support analysis can each play an important part in aiding sports performance analysts
- The exemplars provided may guide some of the various techniques that could be used by performance analysts to address key questions commonly encountered when working in high-performance sport.

CHAPTER 3: Analysis of styles of play according to season and end of season rank in the National Rugby League

Publication

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Author Contributions

C.J.W. contributed 75% to this chapter. He developed the chapter structure, wrote each section, collated and analysed the data. Both C.T.W, M.G. and A.S.L offered conceptual guidance, statistical support and manuscript drafting where required (15%), while W.H.S contributed to the manuscript drafting and construction of ideas within the discussion (10%).

3.1 Abstract

Objectives: This chapter aimed to identify styles of play in the NRL relative to season and end of season rank (position on the NRL ladder) across the 2015-2019 seasons. **Design:** Retrospective, longitudinal analysis of PIs. **Methods:** Forty-eight PIs (e.g. runs, tackles) from all NRL teams and matches during the 2015-2019 seasons (n=2,010) were quantified. Principal component analysis (PCA) was then used to identify styles of play based on dimensions (Factors) of PIs. Multivariate analysis of covariance (MANCOVA) was then used to explain these emergent styles of play relative to 'season' and 'end of season rank'. **Results:** The PCA revealed nine Factors (six attacking, two defensive and one contested style) accounting for ~51% of seasonal team performance variance. These nine Factors differed across 'seasons', with four showing an effect against 'end of season rank'. From these four, two Factors (ball possession and player efforts) impacted upon the combined effects of 'season' and 'end of season rank'. **Conclusions:** The PCA identified nine Factors reflecting a spread of attacking, defensive and contested styles of play within the NRL. These styles differed relative to season and a team's end of season ranking. These results may assist practitioners with the recognition of more contemporary styles of play in the NRL, enabling the development of strategies to exploit competition trends.

3.2 Introduction

Sports performance analysis has become an important practice within high performance environments, as it affords practitioners insight into critical elements of match play, training design, opposition analysis and player selection and recruitment (James, 2006). With the rapid improvement of technologies in sport, the capture and analysis of PIs, through the use of notational or automated analyses, has become more accessible for sporting organisations at all developmental levels (James, 2006). Through such analyses, sporting practitioners have been afforded increased clarity surrounding the resolution of key PIs capable of explaining match events at both team and individual levels (Gomez et al., 2019; Sampaio & Janeira, 2017; Woods et al., 2017d).

Within RL, performance analysis research has focused on aspects of match play inclusive of time and location of ball (re)possession, playing position differences, comparisons of higher and lower ranked teams, and comparisons between elite and sub-elite competition levels (Kempton et al., 2017; Parmar et al., 2018b; Woods et al., 2018b). For example, Parmar et al. (2018a) highlighted the utility of cluster analysis for identifying PIs capable of explaining match outcome in the European Super League. Notably, using PCA, three principal components that best explained match outcome were identified, 'making quick ground', 'quick play' and 'amount of possession' (Parmar et al., 2018a). Undoubtedly, such research has led to greater clarity with regards to training and match strategies intended to improve on-field performance. Interestingly, though, an examination of playing style, like done by Parmar et al. (2018a) is yet to be performed within the NRL.

Style of play in sport has been examined from a competitive and commercial (e.g. commentary, supporters, and the media) perspective (Conlin, 2020; Connolly, 2020; Hewitt et al., 2017). However, it is only recently that the application of analytical approaches intended to better understand the indicators that contribute to teams' style of play has been investigated (Gómez et al., 2018; Hewitt et al., 2017). For example, Fernandez-Navarro et al. (2016) used cluster analysis to identify important groups of technical performance variables that explained the different attacking and defensive styles of play of soccer teams from the Spanish La Liga and the English Premier League. The authors identified six factors which were able to explain 12 different playing styles, whereby 'direct' and 'possession' styles were the most apparent. Further, Lago-Peñas et al. (2018) and Gomez et al. (2019) explored the application of various modelling techniques to identify different playing styles of soccer teams in the Chinese and Greek soccer leagues, respectively. These studies utilised PCA to identify related, high-order performance variables (O'Donoghue, 2008). This information was subsequently used to define team playing style (e.g. attacking or defensively focused), and its relationship with factors such as end of season rank, and seasonal evolution (Gomez et al., 2019).

To date, work is yet to investigate the effect of factors, such as end of season rank and season, has on the emergence of playing styles within the NRL. This is important, as greater clarity with regards to styles of play that differentiate end of season ranking, as well as evolution over time, could enable RL practitioners to better understand and exploit current trends in performance. The aim of this chapter was to identify styles of play within the NRL relative to season and end of season rank across the 2015-2019 seasons.

3.3 Methods

Following a retrospective, longitudinal research design, 48 technical PIs from all 16 teams and matches (n = 1,005 matches) within the NRL during the 2015-2019 seasons were extracted from a licensed central database (Analyzer; The League Analyst, Version

V4.14.318). The technical PIs from full matches and both competing teams were chosen in accordance with previous work (Chapter 5), being shown in full in Table 3. Further, while the array of PIs used in this chapter may not be accessible for readers given licensing restrictions, a reduced selection of the indicators can be found on the following commercial website (www.nrl.com/stats/). As an important footnote to this commercial data, the match data provider for Analyzer (Stats Perform) code PIs during a match in accordance with a listed set of definitions, which are then checked for inaccuracies. The proprietor self-reported reliability of these coded events is >99% (the coefficient of variation being <1%). All procedures were in accordance with ethical approval gained from the local institutional Human Research Ethics Committee (H7968).

Firstly, to identify definable styles of play across the observational period, a PCA was used. Based on the results from Chapter 5 PCA was deemed to be an appropriate technique for reducing the 48 technical PIs into 'n' number of Factors based on their seasonal variance. This is achieved by resolving the eigenvalue, a scaling factor which determines the number (and magnitude) of the principal components used, dropping "less informative" components where necessary. As such, the number of Factors (principal components) retained in the PCA was determined using eigenvalues > 1.2, best resolving the number of Factors and model accuracy. Specifically, by extracting the rotated component matrix (i.e., correlation coefficients between technical PIs and the identified Factors) for values greater than |0.60|, this analysis identified the 'Factors' (combined PIs) that best explained seasonal performance variance across the NRL. Prior to this, a Kaiser-Meyer-Olkin test and Bartlett's test of sphericity confirmed the suitability of the data for factor analysis.

Table 3. Description of assessed technical skill performance metrics.

Technical Performance Metrics	Description
Runs	Attacking player carries the ball into the defensive line
Run Metres	Total distance covered in possession of the ball
Line Breaks	Ball carrier breaks the defensive line during open play OR crosses the try line and scores
Line Break Assists	An action by an attacking player that occurs immediately before a line break from their team mate
Hit ups	Ball carrier runs directly into the tackler, without making an attempt to evade the tackler
Kick Break	An attacking kick that results in the attacking team breaking the defensive line and recovering it further up the field
Tries	Major point score, involves a team placing the ball in a controlled fashion on the ground on between the try-line and the dead ball line of the opposition team (worth 4 points)
Try Assists	The final pass made to a team mate in the lead up to a try being scored
Offloads	Pass attempted whilst being tackled by opposing players
Tackle Breaks	The ball carrier manages to elude the tackler and keeps the ball in play without conceding a tackle
Passes	Ball is thrown by an attacking player to a team-mate
PTB Wins	Attacking player lands on their front, often resulting in a quick PTB for the offensive team
PTB Losses	Tacklers manage to get the attacking player on their back in the tackle, often resulting in a slow PTB.
Tackled Forced Turnover	Loss of possession as a result of a tackle resulting in the opposing team gaining possession of the ball
Pass Turnover	A pass that results in the opposition team gaining possession of the ball
Botched Try	Try scoring opportunity missed, e.g. knock the ball on over the try line
Handling Error	Loss of possession by an attacking player, example: dropped catch, throwing an intercept, losing the ball out, etc.
Decoy	Attacking player near the football that acts as if they may receive the football but don't
Support	Attacking player pushes up with the ball carrier as an attacking option to assist on the play as the ball carrier takes the ball into the line
Meters After Contact	Run meters accrued by the ball carrier after the initial moment of contact from a defender.
Tackles Made	A defensive action that involves physically holding or wresting a player to the ground
Tackles Missed	Unsuccessful tackle attempt made by defensive player
Tackle Forced Turnover	Successful tackle attempt that results in the defending team regaining possession of the ball
Scraps	Player recovers a loose ball
Rambo	Defensive player charges at the opposing kicker in general play in an attempt to impede the kick attempt

Technical Performance Metrics	Description
Intercepts	Defensive player takes possession of the ball off a pass from the opposing team
Try Saves	Defensive action, such as a tackle, that stops an opposing player from scoring a try
Penalty Conceded	Infraction of the rules by a player, resulting in a penalty being awarded to the opposition
Conceded Line break	Defensive action that results in the ball carrier breaking the defensive line during open play OR crosses the try line and scores
Try Cause	Defensive action that results in the opposition team scoring
Kick Defused	Successful recovery of an opposition kick; can be caught on the full or cleaned up from the ground
Failed Kick Defusal	Unsuccessful in the recovery of an opposition kick; may result in a turnover
Kick (total)	An offensive action that involves a player striking the ball with their foot
Kick meters	The distance that a ball covers once kicked by an offensive player
Field Goal Made	Attacking team successfully attempts to drop kick the ball over the crossbar (worth 1 point)
Field Goal Miss	Attacking team unsuccessfully attempts to drop kick the ball over the crossbar
Penalty Made	Successful attempt at goal following a penalty (worth 2 points)
Penalty Miss	Unsuccessful attempt at goal following a penalty
Conversion Made	Successful attempt at goal following a try (worth 2 points)
Conversion Miss	Unsuccessful attempt at goal following a try
Kick Try Assist	An offensive kick that results in a teammate scoring a try
Kick Error	Kick that results in a negative play for the attacking team e.g. Kicked dead, out on the full, etc.
Kick Forced Dropout	Ball is kicked into the defensive teams in-goal area, and forces the defensive side to drop kick the ball back to the opposition from the goal line
Kick Dead	The ball is kicked and leaves the field of play from the in-goal area. The ball is then restarted from the 20m line by the defensive team
Kick Caught in Goal	Defensive player successfully catches the opposing teams kick on the full inside their own in-goal. This results in a 7-tackle set and a 20m restart for the defensive team
Kick 40/20	Ball is kicked from behind the attacking teams own 40m line and goes out between the try line and 20m of the opposing team. The ball must bounce before going out. The ball is then awarded back to the attacking team in the form of a scrum

Secondly, multivariate analysis of covariance (MANCOVA) was used to check factorial differences identified by the PCA across 'season' and 'end of season ranking'. Post-hoc testing involving pairwise comparisons with Bonferroni correction was conducted with significance level set to $p<0.05$. Magnitude of differences across seasons was calculated as effect size (ES) using partial eta square from the MANCOVA with the following effect thresholds: 0.01 = small; 0.06 = medium; and 0.14 = large (Cohen, 1988; Gómez et al., 2018; Smith, 1956). Finally, all descriptive statistics for Factors were represented as mean and standard deviation (mean ± SD). All statistical analyses were carried out using the statistical software IBM SPSS for Windows version 25 (Armonk, NY, USA, IBM Corp.).

3.4 Results

Firstly, the PCA revealed nine Factors (eigenvalues >1.2) that accounted for ~51% of the seasonal variance in team performance (sum of observed technical performance variables) between 2015 and 2019 (see Table 4). The values presented in the rotated component matrix (see Table 5) indicated the strength of the relationship between the various technical performance variables and the nine associated factors. The nine Factors are shown in Table 6 with an associated style of play (based on subjective interpretations and inspection of the PIs grouped into the Factor). Descriptive statistics for these Factors are presented in Table 7.

Table 4. Eigenvalues for principal components identified and total variance explained.

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	6.988	14.559	14.559	6.988	14.559	14.559	5.129	10.685	10.685
2	4.355	9.073	23.632	4.355	9.073	23.632	4.913	10.236	20.921
3	2.491	5.189	28.822	2.491	5.189	28.822	2.316	4.825	25.746
4	2.075	4.323	33.145	2.075	4.323	33.145	2.282	4.754	30.500
5	1.955	4.072	37.217	1.955	4.072	37.217	2.144	4.467	34.968
6	1.878	3.913	41.130	1.878	3.913	41.130	2.050	4.271	39.238
7	1.808	3.767	44.897	1.808	3.767	44.897	2.032	4.234	43.472
8	1.688	3.517	48.413	1.688	3.517	48.413	1.832	3.817	47.289
9	1.381	2.878	51.291	1.381	2.878	51.291	1.656	3.450	50.739
10	1.276	2.657	53.948						
11	1.171	2.439	56.388						
12	1.117	2.328	58.715						
13	1.086	2.263	60.979						
14	1.059	2.206	63.184						
15	1.055	2.198	65.382						
16	1.039	2.165	67.547						
17	.997	2.077	69.624						
18	.984	2.049	71.673						
19	.939	1.956	73.630						
20	.929	1.934	75.564						
21	.897	1.869	77.433						
22	.896	1.867	79.299						
23	.823	1.715	81.014						
24	.795	1.657	82.671						
25	.779	1.623	84.295						
26	.748	1.559	85.854						
27	.669	1.394	87.248						
28	.648	1.350	88.598						
29	.609	1.269	89.867						
30	.594	1.237	91.104						
31	.519	1.082	92.186						
32	.507	1.056	93.242						
33	.465	.970	94.212						
34	.435	.906	95.117						
35	.391	.816	95.933						
36	.349	.726	96.659						
37	.304	.632	97.291						
38	.259	.539	97.830						
39	.214	.446	98.276						
40	.183	.381	98.657						
41	.177	.369	99.027						
42	.175	.364	99.391						
43	.119	.249	99.640						
44	.088	.184	99.824						
45	.064	.133	99.957						
46	.020	.041	99.998						
47	.001	.002	100.000						
48	0.000	0.000	100.000						

Table 5. Rotated component matric for all technical PIs examined; values representing the correlation between each variable and the nine principal components.

	Components								
	1	2	3	4	5	6	7	8	9
Runs	.904	.165	.175	.019	.010	-.026	.001	.059	-.040
Run (m)	.750	.371	.163	.027	.061	-.044	.021	.087	-.026
Line Break	.133	.882	.027	-.062	-.044	-.030	-.137	.017	-.064
Line Break Assist	.126	.855	.032	-.014	-.016	-.007	-.140	-.042	-.010
Hit Ups	.728	.099	.130	.123	-.189	-.034	.042	-.098	.184
Kick breaks	-.019	.120	.005	.003	.017	-.009	.777	-.116	.102
Tries	.043	.909	.082	.096	-.108	-.026	.228	.004	.040
Try Assist	.039	.871	.090	.093	-.068	-.004	.239	-.019	.040
Offloads	.429	.110	-.249	-.374	-.116	.027	-.035	-.027	.055
Tackle Break	.305	.384	.026	-.265	-.038	-.023	.012	.193	-.199
Passes	.840	.019	.127	.064	-.154	-.010	.021	.040	-.085
PTB Win (Attack)	.377	-.002	.065	.108	.078	.001	.014	.866	-.034
PTB Loss (Attack)	.325	.002	.141	.150	.036	-.048	.039	-.872	.049
Tackled FTO	-.143	-.185	.248	-.535	.219	-.004	.005	.040	.150
Pass TO	.102	-.031	-.110	-.350	.025	-.034	-.063	-.029	.046
Botch Try	.024	-.015	.080	.026	-.033	-.017	-.031	.084	-.050
Handling Errors	-.069	-.237	.134	-.777	.049	-.029	.040	.068	.030
Pen Conceded (Attack)	-.035	-.026	.004	.005	-.002	.992	-.005	.008	-.024
Pen Won (Attack)	-.035	-.026	.004	.005	-.002	.992	-.005	.008	-.024
Decoy	.356	-.079	.144	-.067	-.326	.035	-.031	.181	-.450
Support	.252	.022	.225	-.026	-.225	.012	.047	.145	.602
Metres After Contact	.879	.018	.158	.086	.068	-.029	.058	.010	.010
Tackle Made	-.071	-.474	-.072	-.028	.658	-.018	-.124	.082	.061
Tackle Miss	-.126	-.246	-.531	-.124	.005	-.024	-.023	.132	-.074
Tackle Forced Turnover	.132	-.106	.284	.034	-.337	-.025	.048	.185	.438
Scraps	.127	.042	.143	-.082	-.062	.000	.018	-.018	.400
Kick Pressure	.103	-.195	.112	-.069	.429	.038	.023	.118	.600
Intercepts	-.143	.001	-.060	-.214	-.101	-.027	.070	-.030	.025
Try Saves	.006	-.029	-.033	-.068	.087	.001	.017	.032	.429
Pen Conceded (Defence)	-.399	-.063	.130	-.069	-.243	-.071	-.101	.099	.027
Conceded Linebreak	-.211	-.169	-.808	.030	-.074	-.032	-.003	.004	.037
Try Cause	-.301	-.161	-.739	.001	-.083	.020	-.064	-.043	.023
Kick Defused	-.055	-.109	.110	.040	.719	-.001	-.042	-.020	.045
Failed Kick Defusal	.186	-.025	-.038	.025	-.093	.011	.611	.007	-.093
Kick Total	.527	-.158	.145	.607	.239	-.121	.277	.062	.040
Kick (m)	.268	-.099	.148	.574	.445	-.127	.124	.148	-.003
FG Made	.118	-.028	.078	.062	.000	-.006	-.135	.011	.089
FG Miss	.173	-.060	-.075	-.057	.145	.092	-.004	-.014	.120
Pen Made	-.082	-.063	.358	.206	-.250	-.036	-.115	.089	-.061
Pen Miss	.005	-.071	.032	-.031	-.075	-.042	.098	-.010	-.082
Conversion Made	.024	.753	.009	.101	-.138	-.076	.247	.038	-.008
Conversion Miss	.039	.507	.147	.017	.018	.076	.027	-.053	.086
Kick Try Assist	-.029	.243	.072	.084	.001	-.011	.799	.062	.037
Kick Errors	.066	.024	.071	.222	-.011	-.014	-.105	-.128	.219
Kick Forced Dropout	.322	-.101	.253	.176	-.325	-.032	.040	.138	.103
Kick Dead	.074	-.062	-.007	.154	-.046	-.019	.023	-.063	.125
Kick Caught in Goal	.125	-.104	-.111	.092	-.035	.003	-.008	-.088	-.004
Kick 40/20	-.013	.066	.030	.066	.073	.041	.037	-.036	.025

Table 6. Principal components identified with their associated technical performance characteristics and subsequent styles of play.

Factor	Technical PIs	Style of Play
Factor 1 (Runs)	Runs, run metres, passes, hit ups, metres after contact, kick total;	Attacking Play
Factor 2 (Scoring Actions)	Line breaks, line break assists, tries, try assists, conversions made;	Attacking Play
Factor 3 (Try Causes)	Conceded line break, try cause;	Defensive Play
Factor 4 (Last Play Kicking)	Handling errors, kick total;	Attacking Play
Factor 5 (Tackling)	Tackles Made	Defensive Play
Factor 6 (Penalties)	Penalty conceded (attack), penalty won (attack);	Contested Play
Factor 7 (Kick Try Assist)	Kick breaks, failed kick defusal, kick try assist;	Attacking Play
Factor 8 (PTB Won and Lost)	PTB win (attack), PTB loss (attack);	Attacking Play
Factor 9 (Effort Plays)	Kick Pressure, Supports	Attacking Play

PTB = Play The Ball; Descriptors of technical performance characteristics (see Table 1).

Table 7. Descriptive statistics for all Factors identified via PCA relative to match time for each season.

	2015		**2016**		**2017**		**2018**		**2019**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Factor 1 (Runs)	0.05	0.99	0.03	1.00	-0.03	1.00	-0.25	0.98	0.21	0.97
Factor 2 (Scoring)	0.09	0.99	0.11	1.08	0.01	0.99	-0.08	0.98	-0.13	0.93
Factor 3 (Try Causes)	0.06	0.98	-0.22	1.08	0.03	0.94	0.13	0.96	0.00	1.00
Factor 4 (Last Play Kicking)	0.34	1.02	0.00	0.90	-0.20	0.96	-0.11	1.04	-0.03	0.98
Factor 5 (Tackling)	0.05	0.95	0.06	0.98	-0.16	0.96	-0.27	1.04	0.33	0.97
Factor 6 (Penalties)	-0.08	0.92	0.06	1.04	-0.06	0.93	0.09	1.13	-0.01	0.95
Factor 7 (Kick Try Assist)	-0.24	0.92	0.12	1.12	0.23	1.12	-0.15	0.83	0.05	0.90
Factor 8 (PTB Won and Loss)	-0.33	0.68	-0.47	0.99	-0.40	0.92	0.68	0.80	0.55	0.92
Factor 9 (Effort Plays)	0.57	0.78	0.60	0.96	-0.44	0.90	-0.53	0.82	-0.20	0.88

Negative values indicate a reduced occurrence of the combined variables for that factor in that year (relative to time played) compared to the prior year.

Secondly, the results of the MANCOVA revealed differences for each Factor when compared across ‘seasons’ (Table 8). The results of the pairwise comparisons, however, indicated only four Factors were different (small effects) when compared with end of season rank (Table 8): Factor 3 (‘Try Causes’; conceded line break, try cause), Factor 4 (‘Last Play Kicking’; handling errors, kick total), Factor 8 (‘PTB won and lost’; PTB won and lost in possession) and Factor 9 (‘Effort plays’; kick pressure, supports). Further, when examining the between factor interaction effects (season x end of season ranking), only Factor 8 (medium effect) and Factor 9 (medium effect) were different across season and end of season ranking.

The descriptive statistics for end of season ranking and each of the nine Factors identified are shown in Table 9. There were no observed differences in Factor 1 (‘Runs’; runs, run metres, passes, hit ups, metres after contact, kick total), Factor 4 (‘Last play kicking’; handling errors, kick total;), Factor 5 (‘Tackling’; tackles made) and Factor 9 for end of season rank. Upon closer review of the MANCOVA results, the top half of the competition (end of season rankings of 1-8) exhibited a greater average number of ‘Scoring actions’ (Factor 2) compared to the bottom half (end of season rankings of 9-16) of the competition. Further, the top four teams exhibited a negative average for ‘Try causes’ (Factor 3) while teams ranked ninth through twelfth showed the greatest number of penalties (won and conceded) (Factor 8) compared with the rest of the competition.

Table 8. MANCOVA results for all Factors identified from the PCA in terms of season, end of season rank and their combined effects

	SS	df	MS	F	Sig.	η_P^2	ES interpretation
Season							
Factor 1 (Runs)	43.57	4	10.89	11.15	<0.01	0.02	Small
Factor 2 (Scoring Actions)	18.24	4	4.56	4.64	<0.01	0.01	Small
Factor 3 (Try Causes)	29.10	4	7.28	7.85	<0.01	0.02	Small
Factor 4 (Last Play Kicking)	68.86	4	17.22	18.09	<0.01	0.04	Small
Factor 5 (Tackling)	84.55	4	21.14	22.41	<0.01	0.05	Small
Factor 7 (Kick Try Assist)	60.69	4	15.17	15.64	<0.01	0.03	Small
Factor 8 (PTB Won and Lost)	477.89	4	119.47	178.44	<0.01	0.27	Large
Factor 9 (Effort Plays)	487.01	4	121.75	168.14	<0.01	0.26	Large
End of Season Rank							
Factor 3 (Try Causes)	23.452	15	1.563	1.688	0.047	.013	Small
Factor 4 (Last Play Kicking)	31.182	15	2.079	2.184	<0.01	.017	Small
Factor 8 (PTB Won and Lost)	33.68	15	2.25	3.35	<0.01	0.03	Small
Factor 9 (Effort Plays)	39.76	15	2.65	3.66	<0.01	0.03	Small
Season x End of Season Rank							
Factor 8 (PTB Won and Lost)	180.04	59	3.05	4.56	<0.01	0.12	Medium
Factor 9 (Effort Plays)	82.88	59	1.41	1.94	<0.01	0.06	Medium

Column Descriptors (SS – sum of squares; df – degrees of freedom; MS – mean square; F – F statistic; Sig. - significance; η_P^2 – partial eta squared; ES – effect size). Factor descriptors (see Tables 3 and 4).

Table 9. Descriptive statistics for each Factor identified by PCA by individual and group End of Season ranking.

	Factor 1 (Runs)		Factor 2 (Scoring)		Factor 3 (Try Causes)		Factor 4 (Last Play Kicking)		Factor 5 (Tackling)		Factor 6 (Penalties)		Factor 7 (Kick Try Assist)		Factor 8 (PTB Speed)		Factor 9 (Effort Plays)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Rank 1	0.04	1.08	0.17	1.19	0.03	1.07	0.17	0.90	-0.04	0.99	-0.06	0.95	-0.03	0.93	0.07	1.27	-0.21	0.89
Rank 2	-0.14	0.99	0.08	1.04	0.12	0.94	-0.12	0.89	-0.12	1.06	0.13	1.08	0.01	1.06	-0.14	0.96	-0.18	0.82
Rank 3	-0.03	1.02	0.11	0.93	-0.05	0.86	0.06	0.96	-0.16	1.05	-0.06	0.93	0.00	1.01	-0.43	1.03	0.06	0.96
Rank 4	-0.09	1.00	0.02	0.91	-0.01	0.96	0.04	0.91	-0.02	0.98	-0.02	0.92	0.14	1.22	0.05	0.87	0.22	0.99
Rank 5	0.06	0.97	-0.06	0.97	0.10	1.02	-0.08	1.03	0.00	0.94	-0.09	0.95	0.02	0.97	-0.11	0.94	0.06	1.06
Rank 6	0.12	1.08	-0.01	0.95	0.15	0.90	-0.18	1.10	0.02	1.05	0.04	1.01	-0.11	1.02	0.04	0.95	0.12	1.04
Rank 7	0.02	0.97	0.03	0.90	-0.03	0.96	-0.22	0.95	-0.06	0.83	-0.08	0.89	-0.05	0.94	-0.05	1.13	0.05	0.89
Rank 8	0.02	0.93	0.04	1.04	0.01	1.00	-0.02	0.90	0.12	1.01	-0.08	0.89	-0.02	0.96	-0.08	0.92	0.12	1.01
Rank 9	-0.02	1.02	0.11	1.08	0.04	1.09	0.15	0.99	0.12	1.00	-0.03	0.93	-0.02	0.98	0.26	0.85	-0.13	1.05
Rank 10	0.03	0.94	-0.09	1.11	0.04	1.04	-0.02	0.97	-0.23	0.99	0.18	1.10	-0.06	0.87	0.05	1.14	-0.23	1.07
Rank 11	-0.14	1.02	-0.05	1.04	0.08	1.11	-0.03	1.13	0.01	1.01	-0.05	0.98	0.14	1.06	-0.02	1.10	-0.06	1.14
Rank 12	-0.04	0.99	-0.15	1.00	-0.03	1.18	0.07	0.92	0.06	1.03	0.11	1.01	-0.03	1.00	0.00	0.87	0.08	0.99
Rank 13	-0.04	1.08	0.00	0.95	-0.12	1.04	-0.05	1.09	0.14	1.08	-0.01	0.97	-0.08	0.99	-0.09	0.99	-0.14	0.95
Rank 14	0.00	0.95	-0.08	0.82	-0.02	0.88	0.28	1.09	0.04	0.98	0.16	1.43	0.12	0.98	0.19	0.84	-0.07	1.02
Rank 15	-0.07	0.97	-0.05	0.93	-0.04	0.83	0.06	1.05	0.08	1.01	-0.16	0.86	0.12	1.03	0.08	0.95	0.14	0.92
Rank 16	0.24	0.96	-0.06	1.05	-0.35	1.03	-0.06	1.01	0.02	0.94	0.00	0.96	-0.14	0.90	0.14	0.97	0.13	1.05

3.5 Discussion

The aim of this chapter was to identify styles of play in the NRL relative to season and end of season ranking across the 2015-2019 seasons. Overall, results indicated that: (i) team styles of play changed across the observational period; and (ii) different styles of play were evident when a team's end of season ranking was considered. These findings were similar to that observed in soccer (Fernandez-Navarro et al., 2016; Gómez et al., 2018; Lago-Peñas et al., 2018) highlighting the importance of identifying specific styles of play and their impact on end of season ranking. Specifically, three attacking ('last play kicking', 'PTB won and lost' and 'effort plays') and one defensive ('try causes') styles of play were observed to have changed relative to end of season ranking. The current chapter has extended prior work through the identification of seasonal evolution with regards to emergence of a predominant attacking style of play in the NRL.

Collectively, nine Factors explained ~51% of total performance variance within the NRL across the observational period. It was previously reported that teams capable of attaining more meterage with ball in hand were more likely to be successful (Woods et al., 2017d). The results of the current chapter support these findings, having identified that attacking styles of play leading to more 'runs' (Factor 1: runs, run metres, passes, hit-ups, metres after contact and total kicking distance) and 'scoring actions' (Factor 2: line breaks, line break assists, tries, try assists and conversions made) were the most important factors for differentiating team styles of play, accounting for ~15% and 9% of total variance of NRL teams, respectively. In fact, of the nine Factors identified, six (Factors 1, 2, 4, 7-9) were attacking focused with two being defensive (Factors 3 and 5) and one considered as contested (Factor 6; penalties). Further, 'try causing actions' (Factor 3), 'last play kicking actions' (Factor 4), 'PTB won and lost in attack' (Factor 8) and 'effort plays' (Factor 9) influenced a team's end of season ranking. Based upon these Factors, coaching and performance staff could develop match-principles around exploiting the strengths and weaknesses of these identified (predominately attacking) styles of play. This could elicit a positive response (i.e., winning) and thus improve teams' chances of obtaining a favourable end of season ranking.

It has been suggested that elite sporting teams employ a 'follow the leader' type response during competitive seasons, whereby teams constantly adjust their styles of play to reflect that of the competition leaders (Woods et al., 2018b). It would be expected that team's performance characteristics would be in a constant state of flux season-to-season, as teams attempt to replicate or anticipate a dominant 'style of play'. Our results support this proposition, identifying a small effect of season on Factors 1-7, and a large effect for Factor 8 (PTB won and lost) and Factor 9 (Effort Plays). Across seasons, the total number of PTBs (won and lost) progressively increased, reflecting a greater number of PTBs won compared to PTB losses (due to the inverse relationship between PTB won and lost, Table 7). Contextually, this emerging 'style of play' may indicate more attacking players landing forward in a tackle, resulting in a faster play of the ball for the attacking team that restricts the opposing team's time to set their defensive line. Conversely, there was a gradual decline of Effort Plays, whereby players reduced their supporting runs and/or application of kick pressure. Potentially, the reduction in Effort Plays resulted from competition rulings imposed (e.g. the obstruction ruling), leading to fewer supporting runs for fear of incurring an infringement. Whilst this reduction may not be a deliberate tactical shift in team play and more so dependent on external factors, the increase in the number of PTBs across the seasons' suggested teams were placing a greater emphasis on speeding up the match in an attempt to manufacture more scoring opportunities. Exemplifying this, top ranked teams had a greater occurrence of PTB won and lost, and concomitant greatest number of 'scoring actions' (Factor 2) when compared to the rest of the competition. Further supporting the notion that teams regularly adjust their styles of play to reflect that of the competition leaders, and that these leaders are often more successful at doing so (Woods et al., 2018b).

Whilst both Factors 8 and 9 changed across the observational period, it is important to highlight those factors which did not (Factors 1-7). Recognising Factors that did not change may be an important starting place for teams to build a foundation for team success, before attempting to manipulate the changes (or trends) in team styles of play. As shown previously (Parmar et al., 2018a; Woods et al., 2018b), teams that controlled possession and exhibited greater attacking play (Factors 1, 2, 4, 7-9) and reduced defensive mistakes (Factors 3 and 5), had a greater chance of achieving a winning team performance. Using the current and prior information, practitioners could develop training and match-play strategies suited to elicit similar team performance, subsequently affording the greatest chance of winning matches in this competition.

Data reduction techniques, such as PCA, have distinguished physical and technical performance demands in a range of sporting competitions such as soccer (Gómez et al., 2018; Lago-Peñas et al., 2018; Yang et al., 2018), basketball (Gomez et al., 2014; Sampaio et al., 2018) and European Super Rugby (Parmar et al., 2018a). The use of this analysis for the NRL presently further demonstrates the suitability of analogous analytical techniques for match style resolution. For example, sports practitioners could resolve playing styles of their opposition, enabling greater support around decisions relating to preparation and subsequent team selection. Further research exploring the utility of these analytical approaches for match style resolution will offer greater clarity around current individual and team performance characteristics, and subsequent scope for manipulating league-wide trends to maximise a team's likelihood of success in the NRL.

Despite the novelty of this chapter and its findings, it is not without limitations that require discussion. Specifically, our analysis did not consider contextual variables, such as score differential or match location. The effects of such contextual factors have been documented across various sports and is worthy of future consideration in RL (Almeida et al., 2014; Baghurst et al., 2008; Gomez et al., 2008; Legaz Arrese et al., 2013). Further, it is important to note the large amount of team performance variance (~49%) that was unaccounted, which is in direct contrast with similar work in RL (Parmar et al., 2018a). It is possible that other contextual information such as team form, match location and comparative ladder positioning (Parmar et al., 2018a) may be critical for greater predictive accuracy in these analyses. Additionally, the data utilised in this chapter was extracted over a relatively short timeframe and may not be reflective of long-term evolutionary changes (Woods et al., 2018b). Thus, further exploration of team playing styles in RL should consider the impact of contextual factors (e.g. match location or score differential) and extend the observational period beyond five seasons to provide greater clarity about factors important for current and future success.

3.6 Conclusions & Practical Implications

The primary focus of this research was to identify current playing style(s) in the NRL over recent seasons. It was evident that the prominent styles of play in the NRL were predominately attacking and focussed in particular on possession and scoring characteristics. Further, it was apparent that there was a recent shift in the manipulation of teams' styles of play with an increased focus in attacking PTB (wins) in an attempt to increase attacking opportunities on the proceeding play. Conversely, recent changes to the adjudication of rules may have led to the reduction in 'effort plays' from teams in an effort to reduce unforced turnovers through rule violations. These results may better enable coaching and performance staff to augment training and match-principles to exploit the strengths and weaknesses of these identified (predominately attacking) styles of play.

This chapter further highlighted the utility of data reduction techniques, such as PCA, for the identification of teams' styles of play, particularly in the context of the NRL. Despite the successful application of these techniques, further research should also consider the addition of other technical/tactical and even contextual information (e.g. match location) to further identify how NRL playing styles may be augmented by different constraints. For example, given the current emphasis on increasing attacking PTB wins, is the emphasis on this area of the game increased (or decreased) depending on match location (i.e., Home or Away). In this instance, the tactical game-planning required by coaches as the home (or away) team might involve a greater focus on tackle technique/efficiency in order to slow the tackle, and subsequently reduce the number of attacking PTB wins for the opposition. Continuing examination of teams' styles of play, and the impact of contextual factors on these styles, will enable greater decision making for coaching and performance staff for future success.

3.7 Key Points

- Current playing styles in the National Rugby League exhibit a largely attacking focus (eg more 'runs' and 'scoring actions') with defensive and contested playing styles appearing less influential.
- Using the contemporary styles of play identified in this chapter, coaching and performance staff could develop various training and match-principles around exploiting the observed (predominately attacking) styles of play to improve the likelihood of team success.
- The analytical approaches used in this chapter could be applied to other team sports, providing insight into current playing styles representative of their competition.

CHAPTER 4: Exploring the effect of various match factors on team playing styles in the National Rugby League

Publication

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Author Contributions

C.J.W. contributed 75% to this chapter. He developed the chapter structure, wrote each section, collated and analysed the data. Both C.T.W, M.G. and A.S.L offered conceptual guidance, statistical support and manuscript drafting where required (15%), while W.H.S contributed to the manuscript drafting and construction of ideas within the discussion (10%).

4.1 Abstract

Objectives: This chapter examined the effect of match location, score-line, team quality and match outcome on the expression of team playing styles in the NRL across the 2015-2019 seasons. **Methods:** Thirty-eight PIs (e.g. offloads, runs) from all NRL games (n=2,010) were collected. Match-related factors examined were location (home/away/neutral), match type (absolute score differential), team quality (end of season ladder position) and outcome (win/draw/loss). Factor analysis using PCA were run to identify team playing styles, which were inferred from the clustered dimensions (Factors) of team PIs. Discriminant analysis was then used to determine the effect of the match factors on team playing styles. **Results:** PCA revealed nine Factors accounting for ~54% of team performance variance. Discriminant analysis did not meaningfully resolve team playing styles for match type, team quality or location (~34%, ~46% and ~58% classification accuracy, respectively). One discriminant function correctly classified ~81% of matches based on outcome, including four team playing styles defined as 'attacking play', 'linebreaks', 'handling errors' and 'conceded linebreaks'. **Conclusions:** Team playing styles characterised by 'attacking play' and 'linebreaks', coupled with relative defensive efficiency showed the greatest association with winning regardless of team quality, match location or match type. Using similar sport analytical techniques, additional insight into the importance of various team playing styles over the time-course of a match may allow teams to further extrapolate the likelihood of success in real-time.

4.2 Introduction

Rugby league match play is complex, requiring the continual strategic (re)organisation of players in response to a range of constantly evolving and interacting constraints (Lago-Peñas et al., 2018; Ribeiro et al., 2019). In an attempt to manage this complexity, it is common for teams to develop principles of play in certain phases of the match, such as in attack or defence (Ribeiro et al., 2019). Such principles intend to guide team behaviour, while enabling players with the freedom to exploit opposition weaknesses and improve their chances of success (Kempton et al., 2016; Woods et al., 2018b; Woods et al., 2017d). Despite these principles typically promoting adaptable and flexible tactical patterns (Mckay & O'Connor, 2018), team tendencies may still be observable across the various phases of match-play (i.e., attack or defence). The resolution of these team tendencies (herewith referred to as 'playing styles') could lead to a considerable performance advantage in practice.

Research across several sports has focused on the resolution of team playing styles using a variety of different metrics (Fernandez-Navarro et al., 2016; Gomez et al., 2008; Woods et al., 2017d). For example, various attacking and defensive playing styles were identified for soccer teams from the Spanish La Liga and the English Premier League (Fernandez-Navarro et al., 2016). Additionally, the influence of various match-related factors on team playing styles, such as location (home and away) (Almeida et al., 2014; Courneya & Carron, 1992; Gomez et al., 2009), match type (score-line) (Sampaio & Janeira, 2017; J. Sampaio et al., 2010; Teramoto & Cross, 2010) and team quality (Almeida et al., 2014; Woods et al., 2017d), have also been applied practically in a range of sports. For example, Yang et al. (2018) highlighted that top-ranked teams exhibited greater technical skill outcomes (e.g., maintaining possession, 50-50 challenges, fouls committed) relative to lower-ranked teams in the Chinese Super League. Further, Almeida et al. (2014) observed that when playing at home in the UEFA

Champions League (soccer), lower-ranked soccer employed a more passive defensive strategy when losing, whereas higher-ranked teams employed more proactive strategies, regardless of match score-line. The effects of match location on team performance in basketball identified that winning teams executed more defensive rebounds, assists and successful two-point field goals when playing away (Gomez et al., 2008). Research in Rugby Union highlighted that in both close (0-11 points differential) and balanced (12-25 points differential) competition matches, winning teams exhibited more kicks, kicks to touch, tackles made and fewer errors than losing teams (Vaz et al., 2011). On the other hand, at an international level (World Cup and Six Nations), there were no significant differences between winning and losing teams in close matches (Vaz et al., 2011). The above studies highlight the importance of various match-related factors on team performance that need to be considered, particularly in regard to playing styles.

Extending on the above literature for a RL context, the effects of team form (competition points collected from previous five matches) and ladder position (end of season rank) were observed in the European Super League (Parmar et al., 2018a). Parmar et al. (2018a) revealed that teams that controlled possession and increased component scores for "making quick ground" and "quick play", were more likely to win. More recently, I identified in that NRL teams predominately focused on an 'attacking' style of play with three attacking and one defensive styles of play able to explain team performance variance according to team quality (Chapter 5). To date, the effect of additional match-related factors on team playing styles is yet to be investigated in the NRL. As shown in other team sports (Greenham et al., 2017; Lago-Peñas et al., 2018; Zhang et al., 2019), such research may enable novel insights into the effect of match factors on team playing styles, enabling teams to reorganise team principles of play based on such context (Hewitt et al., 2017). For example, Zhang et al. (2019) showed that 'dominant' teams in the National Basketball Association (NBA) exhibited similar playing styles across the course of the season. Specifically, the two teams that competed in the finals were clustered together, which indicated that both teams experienced similar changes in their playing styles across the course of the NBA season (Zhang et al., 2019). Subsequently, the aim of this chapter was to examine the effect of various match-related factors on team playing styles in the NRL.

4.3 Methods

Thirty-eight team technical PIs from all sixteen teams were extracted from a licensed central database (Analyzer; The League Analyst, Version V4.14.318) across all matches (n=1,005) during the 2015-2019 NRL seasons, equating to 2,010 individual team performances. As reported in Chapters 3 and 5 and by others (Woods et al., 2018b; Woods et al., 2017d), the technical PIs from full matches and both competing teams were used to characterise team playing styles for each phase of match play as offensive (attacking), defensive or transitional (actions involving changing of possession, i.e. kicks) (Table 10). All technical PIs were chosen in consultation with NRL coaching staff, with those indicators directly reflecting scoring (e.g. tries, try assists, or conversions made) omitted from the analysis to reduce any bias of these factors on team playing style(s). A sample list of technical PIs was available at www.nrl.com/stats/ with the full list restricted to licensed NRL clubs. All competitive NRL matches were coded live by Stats Perform according to a pre-determined set of definitions and then checked for inaccuracies. The self-reported reliability of this coding process was >99% according to Stats Perform.

In addition to the chosen technical PIs, the following match-related variables (response variables) were also analysed: 1) match location (Home / Away / Neutral); 2) match type (absolute score margin; |team score – opposition score|); 3) team quality (end of season ladder position); and 4) match outcome (Win / Loss / Draw) (Gómez et al., 2018; Tenga & Sigmundstad, 2011). All data was collated and analysed in accordance with approval from the local institutional Human Research Ethics Committee (H7968).

4.3.1 Statistical Analyses

Three statistical approaches were used to address the aim: (1) two-step cluster analysis; (2) Factor analysis using principal component analysis (PCA; and (3) discriminant function analysis. Firstly, two-step cluster analysis was used as an unsupervised approach to identify groups based on the different response variables (e.g., match type, team quality, etc). The cluster analysis was employed to automatically determine the "optimal" number of clusters via the Schwartz's Bayesian Information Criterion (BIC) (Wendler & Gröttrup, 2016). In order to determine the "goodness" of the clustering, the silhouette coefficient (≥ 0.7) was examined as a measure of cluster cohesion and separation (Wendler & Gröttrup, 2016). Additionally, the log-likelihood distance measure was used to identify the similarity between clusters (Wendler & Gröttrup, 2016).

Table 10. Attacking, defensive and transitional technical PIs with their associated descriptors.

Technical Performance Metrics	Description
Attacking Variables	
Runs	Player in possession of the ball carries the ball forward towards the opposition defensive line
Run Metres	Total distance covered by the player in possession of the ball
Line Breaks	Player in possession of the ball breaks the defensive line during open play
Line Break Assists	An action by an attacking player resulting in a teammate line breaking i.e., pass or kick
Hit ups	Player in possession of the ball carries directly into the opposing defensive line
Kick Break	An attacking kick resulting in the attacking team breaching the opposition's defensive line and recovering the ball further up field
Offloads	Ball successfully passed whilst being tackled by opposing players
Tackle Breaks	Ball carrier eluding the tackler and keeps the ball in play without conceding a tackle
Passes	Ball is thrown backwards by an attacking player to a team-mate
PTB Wins	Attacking player landing on their front in a tackle
PTB Losses	Tacklers manage to get the attacking player on their back in the tackle
Tackled Forced Turnover	Loss of possession as a direct result of a tackle
Pass Turnover	Pass error that results in the opposition gaining possession
Botched Try	Missed try scoring opportunity
Handling Error	Loss of possession by an attacking player
Decoy	Attacking player running near the football acting as if they may receive the football but doesn't
Support	Attacking player pushes up with the ball carrier as an attacking option to assist on the play as the ball carrier takes the ball into the line
Meters After Contact	Run meters accrued by the ball carrier after the commencement of a tackle from a defender
Handling Errors	
Defensive Variables	
Tackles Made	A defensive action that involves halting the momentum of an opposing player carrying the football
Tackles Missed	An unsuccessful tackle attempt
Tackle Forced Turnover	Tackle attempt resulting in the defending team gaining possession of the ball as a direct result of an attacker error in the tackle
Scraps	Player recovers a loose ball
Rambo	Defensive player charges at the opposing kicker in general play in an attempt to impede the kick attempt
Intercepts	Defensive player collecting the ball off a pass from the opposing team
Try Saves	Defensive action, such as a tackle, that directly stops an opposing player from scoring a try
Penalty Conceded	Infraction of the rules by a player, resulting in a penalty being awarded
Conceded Linebreak	Ineffective defensive action that results in the ball carrier breaking the defensive line during open play OR breaching the the try line and scores
Transitional Variables	
Kick Defused	Successful recovery of an opposition kick (caught on the full or retrieved from the ground)
Failed Kick Defusal	Unsuccessful recovery of an opposition kick
Kick (total)	A player striking the ball with their foot
Kick meters	Distance a ball covers once kicked
Kick Error	Kick that results in a negative play for the attacking team
Kick Forced Dropout	Ball is kicked into the defensive teams in-goal area, and grounded or run dead by a defender, resulting in a drop kick back to the attacking team
Kick Dead	The ball is kicked and leaves the field of play from the in-goal area
Kick Caught in Goal	Defensive player successfully catches the opposing teams kick on the full inside their own in-goal
Kick 40/20	Ball is kicked from behind the attacking teams own 40m line and goes out over the sideline between the try line and 20m of the opposing team (ball must bounce before going out)

Prior to performing PCA, data suitability factor analysis was confirmed using both the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. Given the large number of variables being examined, PCA was used to reduce the total number of observed technical performance variables into 'n' number of dimensions (Factors; eigenvalues > 1.2) (Jolliffe, 2011; Rojas-Valverde et al., 2020). An eigenvalue of >1.2 was deemed most suitable for the authors as it best resolved an appropriate number of Factors, without a major decrement in % variance from an eigenvalue of 1 (Figure 3). More specifically, the threshold utilised for identifying which variables contributed to each Factor, was determined by extracting variables greater than |0.60| from the rotated component matrix (i.e. correlation coefficients). Based on previous research (Chapter 5; Parmar et al., 2018a; Sampaio et al., 2018), these Factors were subsequently saved and then used to identify 'playing styles'.

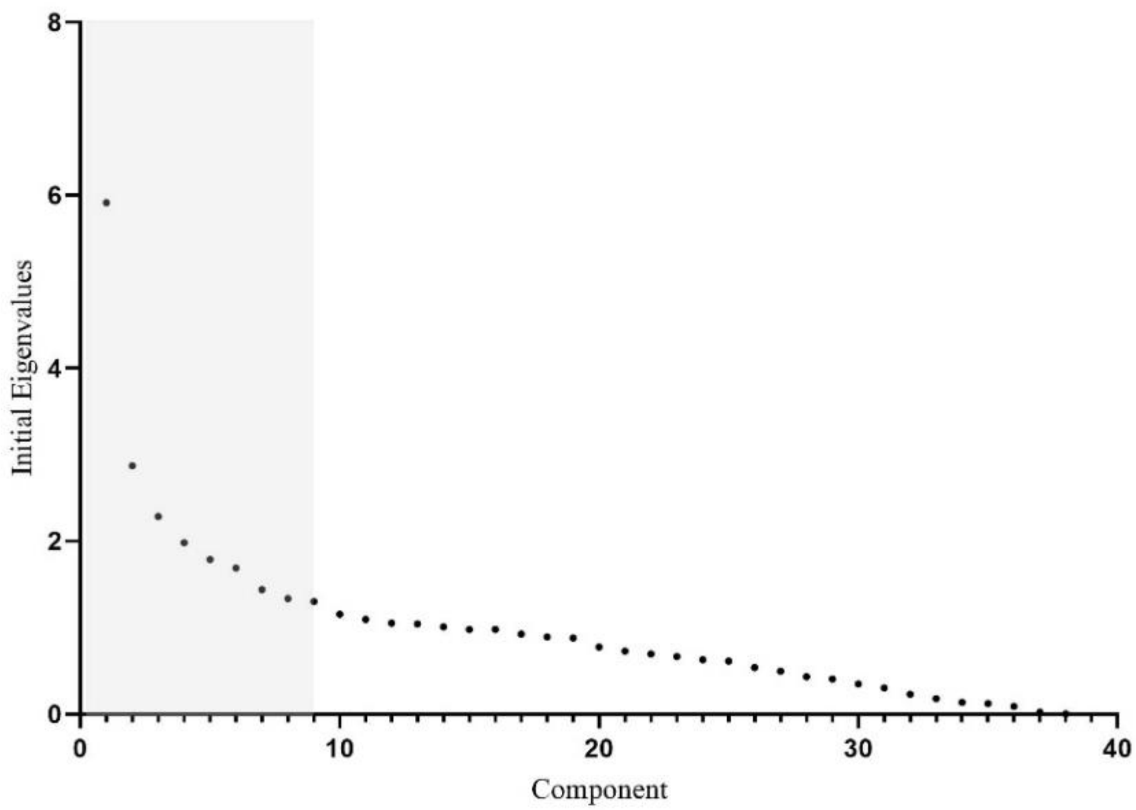

Figure 3. Initial Eigenvalues for principal components identified with components 1 to 9 contributing to 54.2% of total variance (Eigenvalue > 1.2).

Finally, discriminant function analysis was used to identify ‘discriminant functions’ which best explained the interactions between response variables and the identified playing styles (Factors), and the subsequent classification accuracy of these functions (Jolliffe, 2011). The component scores for each of the identified Factors and the additional response variables (i.e. match type; entered as categorical variables from resulting two-step cluster analysis) were all included. Structure coefficient (SC) values greater than |0.30| were considered important for identifying the variance of technical performance variables with the associated response variables (Zhang et al., 2018). All statistical analyses were carried out using IBM SPSS for Windows version 25 (Armonk, NY, USA, IBM Corp).

4.4 Results

Two-step cluster analysis identified four different match types as follows (average silhouette coefficient = 0.7): ‘close’ (35% of all matches, n = 703, absolute margin = 3.2); ‘balanced’ (29.3%, n = 589, absolute margin = 10.7); ‘unbalanced’ (23.3%, n = 468, absolute margin = 20.1); and ‘runaway’ matches (12.4%, n = 250, absolute margin = 35.8). Cluster analysis was additionally performed on team quality, which grouped rankings into top third (33.2%, n = 667), middle third (32.2%, n = 648) and bottom third (34.6%, n = 695).

The PCA model revealed nine factors or playing styles (Table 11) accounting for 54.2% of the total technical performance variance. These nine factors were (Table 12): Factor 1 (‘attacking play’); Factor 2 (‘linebreaks’); Factor 3 (‘errors’); Factor 4 (‘defensive play’); Factor 5 (‘penalties’); Factor 6 (‘PTB won and lost’); Factor 7 (‘conceded linebreak’); Factor 8 (‘supports’); and Factor 9 (‘kick breaks’).

Discriminant function analysis identified one significant discriminant function for match outcome based upon ‘attacking play’ (Factor 1, SC = 0.40), ‘linebreaks’ (Factor 2, SC = 0.71), ‘errors’ (Factor 3, SC = -0.35) and ‘conceded linebreaks’ (Factor 7, SC = 0.66). The re-classification accuracy for match outcome was 80.5% (Figure 4A). Just one discriminant function was identified for match location based upon three significant variables including match outcome (SC = -0.43), ‘attacking play’ (Factor 1, SC = 0.62) and ‘supports’ (Factor 8, SC = -0.37). The re-classification accuracy of match location was 57.5% (Figure 4B). Discriminant analysis for team quality identified two significant functions. Function 1 included ‘match outcome’ (SC = -0.56), ‘linebreaks’ (Factor 2, SC = 0.69) and ‘conceded linebreaks’ (Factor 7, SC = 0.48) while Function 2 included match type (SC = 0.31), ‘linebreaks’ (Factor 2, SC = 0.30), ‘defensive play’ (Factor 4, SC = -0.50) and ‘supports’ (Factor 8, SC = 0.46). Re-classification accuracy for team quality was 46.4% (Figure 4C). Finally, three discriminant functions were identified for match type. Function 1 included; ‘attacking play’ (Factor 1, SC = 0.53) and ‘linebreaks’ (Factor 2, SC = -0.61), Function 2 included match outcome (SC = -0.42), ‘handling errors’ (Factor 3, SC = 0.38), ‘supports’ (Factor 8, SC = 0.34) and team quality (SC = 0.79), and Function 3 included ‘errors’ (Factor 3, SC = -0.61) and ‘supports’ (Factor 8, SC = 0.68). Re-classification accuracy for match type was 33.6% (Figure 4D).

Table 11. Eigenvalues for principal components identified and total variance explained.

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	5.916	15.567	15.567	5.916	15.567	15.567	5.165	13.592	13.592
2	2.873	7.561	23.128	2.873	7.561	23.128	2.532	6.664	20.256
3	2.284	6.011	29.140	2.284	6.011	29.140	2.174	5.721	25.977
4	1.982	5.216	34.356	1.982	5.216	34.356	2.168	5.706	31.683
5	1.788	4.706	39.062	1.788	4.706	39.062	2.041	5.371	37.054
6	1.687	4.438	43.501	1.687	4.438	43.501	1.835	4.830	41.884
7	1.440	3.790	47.291	1.440	3.790	47.291	1.698	4.469	46.352
8	1.336	3.515	50.806	1.336	3.515	50.806	1.648	4.336	50.688
9	1.302	3.427	54.232	1.302	3.427	54.232	1.347	3.544	54.232
10	1.155	3.039	57.272						
11	1.096	2.883	60.155						
12	1.051	2.767	62.922						
13	1.040	2.736	65.658						
14	1.007	2.649	68.307						
15	0.978	2.575	70.882						
16	0.977	2.570	73.452						
17	0.926	2.436	75.888						
18	0.893	2.349	78.237						
19	0.877	2.307	80.544						
20	0.774	2.037	82.581						
21	0.729	1.918	84.499						
22	0.694	1.827	86.325						
23	0.666	1.752	88.078						
24	0.627	1.651	89.729						
25	0.611	1.607	91.336						
26	0.537	1.413	92.749						
27	0.496	1.305	94.054						
28	0.430	1.132	95.186						
29	0.404	1.063	96.249						
30	0.349	0.919	97.168						
31	0.303	0.797	97.966						
32	0.227	0.598	98.564						
33	0.180	0.473	99.037						
34	0.134	0.354	99.390						
35	0.123	0.323	99.713						
36	0.089	0.234	99.946						
37	0.020	0.054	100.000						
38	0.000	0.00	100.000						

Table 12. Identified team playing styles via PCA and the associated technical PIs.

Factor (Playing Style)	Technical PIs	Phase of match-play
Factor 1 (Attacking Play)	Runs (0.920), Run metres (0.772), Hit Ups (0.741), Passes (0.830), Metres After Contact (0.904)	Attacking Play
Factor 2 (Linebreaks)	Linebreak (0.888), Linebreak Assist (0.838)	Attacking Play
Factor 3 (Errors)	Tackled Forced Turnover (0.643), Handling Errors (0.829)	Defensive Play
Factor 4 (Defensive Play)	Tackle Made (0.655), Kick Defused (0.720)	Defensive Play
Factor 5 (Penalties)	Penalty Conceded (in Attack) (0.996), Penalty Won (in Attack) (0.996)	Contested Play
Factor 6 (PTB Won and Lost)	PTB Win (in Attack) (0.855), PTB Loss (in Attack) (-0.847)	Attacking Play
Factor 7 (Conceded Linebreak)	Tackle Miss (-0.623), Conceded Linebreak (-0.720)	Defensive Play
Factor 8 (Supports)	Support (-0.605)	Attacking Play
Factor 9 (Kick Breaks)	Kick Breaks (0.696), Failed Kick Defusal (0.714)	Attacking Play

Descriptors of technical performance characteristics (see Table 3) with associated rotated component score in brackets.

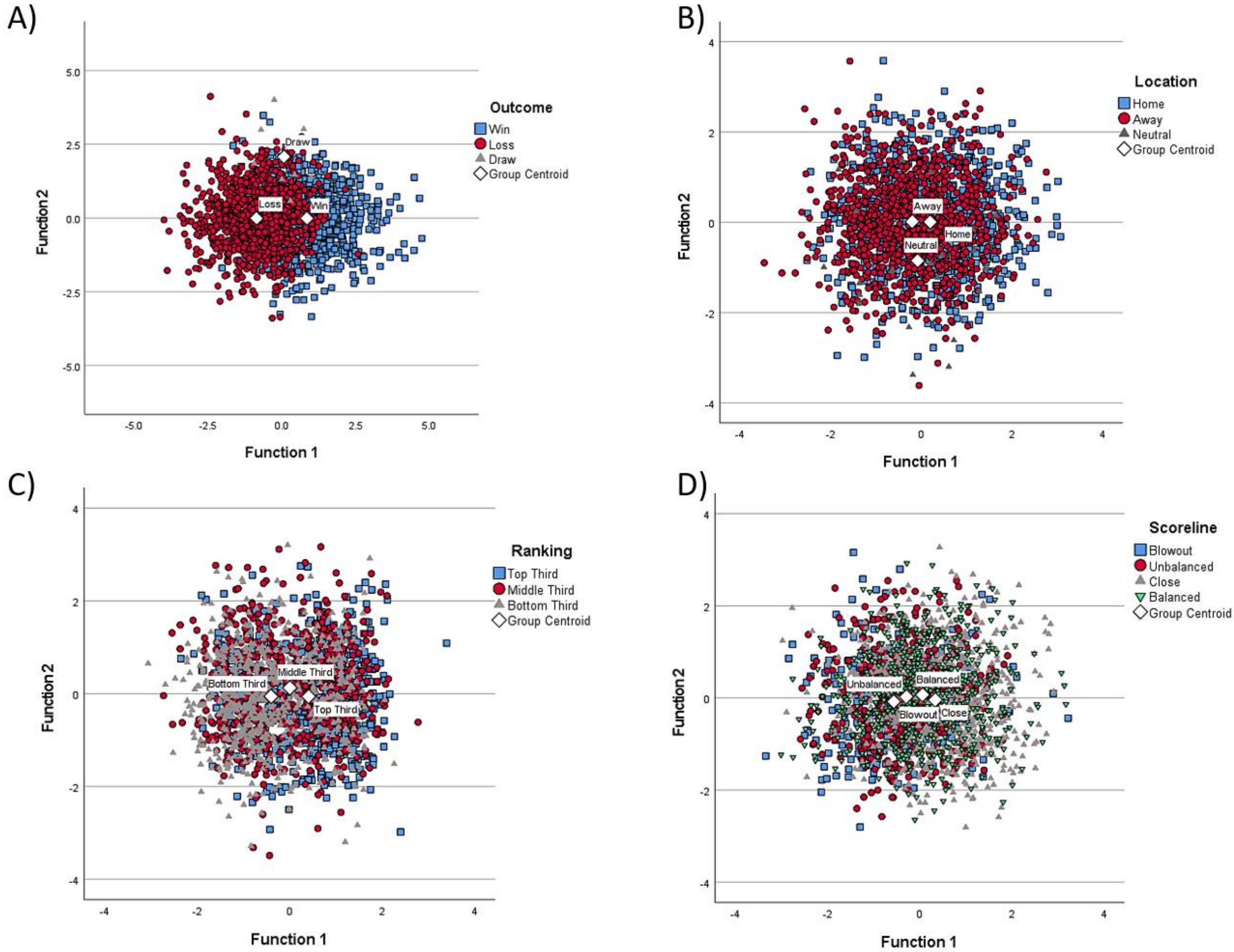

Figure 4. Canonical discriminant function plots for each of the match related factors; A) match outcome, B) match location, C) team ranking, and D) score line.

4.5 Discussion

This chapter examined the effect of match-related factors such as match type, location, team quality and outcome on team playing styles in the NRL across the 2015-2019 seasons. Analysis revealed no significant discriminatory capabilities for three of the four match-related Factors based upon team playing styles (i.e., match type, team quality and location). However, 81% of matches were accurately classified for match outcome, with four playing styles identified as important for discriminating winning and losing performances; 'attacking play' (Factor 1), 'linebreaks' (Factor 2), 'errors' (Factor 3) and 'conceded linebreaks' (Factor 7). While predominant team playing styles relative to all response variables were not identified, the results of the discriminant analysis for match outcome could be further applied in a practical sports setting. For example, evaluating the strengths (and weaknesses) of opponent's predominant styles of play and the importance of these playing styles with regards to winning (and losing) could lead to greater team success in the NRL.

Principal component analysis identified nine playing styles (Factors) that explained ~54.2% of total team performance variance. Previous RL literature reported that teams, which attained more meterage with ball, maintained more possession and generate greater scoring opportunities were more likely to be successful (Parmar et al., 2018a; Woods et al., 2017d). In accordance with this research, the current playing styles involving such metrics (e.g. runs and run metres; Factor 1 'attacking play') were found to be most discriminant for team performance variance (15.6%). Further, actions that contributed to scoring (or score assist), such as 'linebreaks' and 'linebreak assists', were considered the second most important factor for distinguishing team performance (Factor 2 'linebreaks'; 7.6%). In isolation, these playing styles may hold little value however, coaches and performance staff could use this information to aid in the development of training and game strategies to best elucidate these team playing styles and greatly improve their likelihood of winning. For example, implementing set-plays that create player imbalance opportunities in favour of the attacking team could increase the likelihood of linebreaks for the attacking team and subsequently increase metres gained (and a further chance of scoring).

This chapter used discriminant function analysis to observe the effect of the response variables on the expression of team playing styles. Particularly, this analysis showed moderate classificatory power to differentiate team playing styles with regards to three response variables; match type (34% classification accuracy), team quality (46% classification accuracy), and match location (58% classification accuracy, see Figure 4). Whilst the resolution of the discriminant functions for these three match-related factors was moderate, there were some emergent playing styles that partially explained team performance for each of these match factors. For example, match type could be partially explained using four identified playing styles ('attacking play', 'linebreaks', 'errors' and 'supports') in addition to two response variables (team quality and match outcome). Put simply, the higher-ranking teams who exhibited the four identified playing styles were most likely to score more points and be successful in the match. Intriguingly, despite the available research, match location in the current chapter was not an important factor in discriminating team performance with regards to match type, team quality or match outcome. This finding was contrary to what has been observed in other team sports (e.g., soccer, basketball, rugby, handball, etc) where teams were seen to be more assertive and aggressive when playing at home, and more conservatively when playing away (Almeida et al., 2014; Gómez et al., 2011; Sapp et al., 2018). This perhaps suggests that NRL teams do not adopt a specific playing style(s) with regards to match location with further investigations needed to confirm a 'home advantage' for NRL teams.

Discriminant function analysis further identified four independent playing styles important for discriminating winning and losing performance in the NRL (80.5% classification accuracy); ‘attacking play’, ‘linebreaks’, ‘conceded linebreaks’ and ‘errors’. Despite previous studies reporting the effect of various match factors on team success in soccer (Almeida et al., 2014; Gómez et al., 2018; J. Sampaio et al., 2010), the results of this chapter indicated that team success in the NRL was largely unaffected by other observed match factors (i.e., match type, team quality, location). As such, our results indicated that winning teams in the NRL exhibited a specific set of performance variables indicative of successful performance, regardless of context. In this instance, NRL teams had an emphasis on attacking ball control and linebreaks (Factors 1 ‘attacking play’ and 2 ‘linebreaks’) with relative defensive efficiency (Factor 3 ‘errors’ and 7 ‘conceded linebreaks’). Further insight into the importance of various team playing styles across the course of a match would allow teams to further extrapolate the likelihood of team success during a live match. For example, team performance analysts could analyse live-coded match information and feed this quickly to coaching staff on specific variables or playing styles that were (or not) contributing towards a winning team performance.

Whilst this chapter highlighted the utility of unsupervised analytical techniques for the evaluation of team playing styles in RL, there were some limitations that require recognition. It is important to mention the large amount of team performance variance (~46%) that was unaccounted for in the identification of playing styles. This unexplained variance was in direct contrast with similar work in RL (~46% vs. ~18%) (Parmar et al., 2018a). Further, it was also worth noting that only 21 of the 38 (~55%) analysed team PIs were included for further analysis via PCA, and just six of the nine identified ‘playing styles’ were shown to have an effect on team performance dependant on the different response variables, specifically match outcome. These results would suggest that teams did not exhibit a consistent set of playing styles with regards to three of the examined match factors. It is also possible that the chosen technical PIs were not sensitive enough to detect differences in team playing styles with other PIs (e.g., time in possession, consecutive sets, measures of territory gain/field position advantage) possibly providing a greater understanding of team organisation with regards to various match factors. Further exploration of team playing styles in RL may be valuable in elucidating conclusions about team playing styles, team performance variability, and subsequent understanding of factors important for current and future success in RL. Examining the intra- and inter-match variability of team playing styles based on match-related variables (like those identified in this chapter), may provide additional insight into the importance of various team playing styles over the time-course of a match and allow teams to manipulate the likelihood of success in real-time.

4.6 Conclusions & Practical Implications

The findings of this chapter highlighted the lack of resolution for the predominant team playing styles in the NRL with respects to match type, location, and team quality. However, discriminant functional analysis identified that winning and losing in the NRL could be classified using four identified playing styles. Specifically, teams' that placed an emphasis on attacking ball control and linebreaks with relative defensive efficiency (reduced conceded linebreaks) had the greatest likelihood of success in the NRL during 2015-2019. The results from the discriminant functional analysis, specifically match outcome, could be further applied by coaches and performance staff to resolve the likelihood of match success using the identified playing styles. Further investigation into the importance of various team playing styles across the time-course of a live match using similar analyses may allow teams to further extrapolate the likelihood of team success.

Whilst it's important to generate more (and more) information about opposition (and their own) teams' playing styles with regards to winning and contextual factors, it might be equally important to understand how different players/positional groups within these teams contribute to team match performance. Understanding how different positional groups contribute to the overall performance of the team, will subsequently enable coaches and performance staff to make better decisions regarding training planning, personnel selection, and recruitment practices. Using an example from Chapter 3 which highlighted that successful teams produce greater a number of attacking PTB wins, with the prospect of creating ruck speed - teams may need to identify a strong running hooker, who can subsequently exploit a PTB win with their running and create further disorganisation amongst the oppositions defensive. Without understanding the performance characteristics of different positional groups, it's difficult to determine the subsequent impact that each of these positional groups might have on overall team success. Therefore, it is important to determine the performance characteristics of different positional groups prior to examining their subsequent importance to the successful organisation and execution of successful team tactics (structures).

4.7 Key Points

- Using the playing styles identified in this chapter, coaching and performance staff could develop various training and match-principles around exploiting the observed playing styles to improve the likelihood of team success.
- Further application of the results of this chapter could be used to extrapolate the likelihood of team success across the time-course of a live match, enabling 'real-time' strategic adjustment.

- The analytical approaches used in this chapter could be further applied to other team sports, providing insight into identification and importance of current playing styles of their respective competitions

CHAPTER 5: Examining the evolution and classification of player position using performance indicators in the National Rugby League during the 2015-2019 seasons

Publication

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Author Contributions

C.J.W. contributed 75% to this chapter. He developed the chapter structure, wrote each section, collated and analysed the data. Both C.T.W, M.G and A.S.L offered conceptual guidance and statistical support where required (15%), while W.H.S contributed to the manuscript drafting and construction of ideas within the discussion (10%).

5.1 Abstract

Objectives: This chapter aimed to: 1) examine recent seasonal changes in performance indicators for different NRL playing positions; and 2) determine the accuracy of PIs to classify and discriminate positional groups in the NRL. ***Methods:*** 48 PIs (e.g., passes, tackles) from all NRL games during the 2015-2019 seasons were collated for each player´s match-related performance. The following analyses were conducted with all data: (i) one-way ANOVA to identify seasonal changes in PIs; (ii) PCA to group PIs into factors; (iii) two-step cluster analysis to classify playing positions using the identified factors; and (iv) discriminant analysis to discriminate the identified playing positions. ***Results:*** ANOVA showed significant differences in PIs across seasons ($F = 2.3–687.7$; $p = 0-0.05$; partial $\eta2 = 0.00–0.075$). PCA pooled all PIs and identified 14 factors that were included in the two-step cluster analysis (average silhouette = 0.5) that identified six positional groups: forwards, 26.7%, adjustables, 17.2%, interchange, 23.2%, backs, 20.9%, interchange forwards, 5.5% and utility backs, 6.5%. Lastly, discriminant analysis revealed five discriminant functions that differentiated playing positions. ***Conclusions:*** Results indicated that player's performance demands across different playing positions did significantly change over recent seasons (2015-2019). Cluster analysis yielded a high-level of accuracy relative to playing position, identifying six clusters that best discriminated positional groups. Unsupervised analytical approaches may provide sports scientists and coaches with meaningful tools to evaluate player performance and future positional suitability in RL.

5.2 Introduction

Rugby league is a demanding team invasion sport, requiring players to possess a range of physical (Hulin et al., 2015; Twist et al., 2014) and technical (Bennett et al., 2016; Sirotic et al., 2011; Woods et al., 2017d) qualities. Specifically, NRL teams have to perform at the highest level during a very competitive tournament that requires the integration of performance analysis with the intention of describing and identifying teams and player´s performances (Kempton et al., 2016; Woods et al., 2018b; Woods et al., 2017d). The integration of these processes could continue to yield a variety of benefits for high performance staff within the NRL, such as understanding the current team performance trends among the league (Woods et al., 2018b). This may assist with coaching strategies specifically related to game planning and subsequent player selection. Similarly, the ability to understand current positional performance trends could provide a team with advantages during their player recruitment process, such that they can identify and appropriately assess the value of potential player acquisitions – an avenue that is yet to be explored within the NRL.

Previous work in RL has identified PIs capable of differentiating playing position (backs, forwards, fullback, hooker, and service players) (Sirotic et al., 2011). It was observed that forwards, hookers, and service players (halfbacks and five-eighth players) completed more tackles per minute than both backs and fullbacks (Sirotic et al., 2011). When each of the groups was compared for offensive involvements, hookers had the highest count of ball touches, whereas both backs and fullbacks completed more runs with the ball than all other positional groups (Sirotic et al., 2011). A similar study also compared the total number of offensive and defensive actions performed by three different positional groups (forwards, backs, and adjustables) amongst junior RL athletes (Bennett et al., 2016). In this chapter, forwards (props, lock, and back rowers) completed the greatest number of both offensive and defensive actions compared to both adjustables and backs (Bennett et al., 2016). Further, adjustables (halves, hooker, fullback) completed a significantly greater number of defensive and total technical skills compared to the backs (Bennett et al., 2016). Collectively, these studies demonstrated that player's game involvements were likely to vary according to playing position. The implications of this are likely to extend towards practice design, enabling a level of positional representativeness. However, despite these initial findings, it remains unknown whether positional specific attributes in the NRL have evolved over time.

Several studies have identified player's performance from a medium-term perspective in soccer (Bush et al., 2015) and AF (Woods et al., 2018c; Woods et al., 2017e). In soccer for example, compared to attackers and wide players, central players increased their involvement in play through a greater increase in the number of passes made and pass success rate (Bush et al., 2015). More specifically, centre midfielders and fullbacks increased the number of short and medium distance passes from the 2006-07 to 2012-13 season (Bush et al., 2015). Furthermore, despite large player homogeneity across various positional demands in junior AF (Woods et al., 2018c), when combined with physical performance measures, clearer associations between higher and lower ranked draftees were identified (Woods et al., 2017e). Understanding that the demands of sport may change over time (Woods et al., 2018a; Woods et al., 2018b), and having systems in place to monitor and adapt to these changes, is crucial to ensure that contemporary training and game strategies are implemented to enhance a team's chances of success (Robertson et al., 2017).

Due to the large number of PIs available to NRL teams, it is important to understand which of these are explanatory of a successful performance. Performance modelling involving analytical approaches such as factor reduction, clustering and discriminant analysis have previously been used to differentiate playing positions and the importance of various PIs in multiple sports (Lago-Peñas et al., 2018; Sampaio et al., 2018; Zhang et al., 2018). These approaches enable the closer inspection of the relationships that exist between both performance variables and positional groups (Sampaio et al., 2018; Zhang et al., 2018). Pertinently, such analytical approaches are capable of resolving clusters of attributes that explain specific aspects of performance, as well as identifying different positional types that may not be typically understood by coaching staff (Sampaio et al., 2018; Zhang et al., 2018). For example, three positional groups (guards, forwards, and centres) have been historically identified within basketball. However, using clustering techniques, six different positional groups were identified via technical basketball performance data (Sampaio et al., 2018) and five different groups using only anthropomorphic data (Zhang et al., 2018). As such, it may be important to consider novel performance modelling techniques when exploring the various demands of RL performance in order to better understand the relationships between different positional groups and their PIs. Previous work in RL has observed differences in positional technical performance demands using a select number of technical variables (Bennett et al., 2016; Sirotic et al., 2011). Additionally, changes in collective team PIs have been identified between the 2005-2011 and 2012-2016 NRL seasons (Woods et al., 2018b). However, it is unclear whether the positional specific demands of RL athletes differed across seasons, or whether there was relative positional stability over time. Overall technical performance demands of teams in the NRL were reported to have evolved (Woods et al., 2018b), which may subsequently have led to a change in the positional demands of NRL athletes, however, this is yet to be identified.

The aim of this chapter was to investigate whether technical performance demands of different positional groups in the NRL had changed over recent years (2015-2019), and whether playing positions could be accurately classified and discriminated using PIs from the NRL. Findings could assist coaches in understanding the current trends of positional technical performance demands, and subsequently improve decision making with regards to game strategy, training planning and personnel selection.

5.3 Methods

Forty-eight PIs were collected from a licensed central database (Analyzer; The League Analyst, Version V4.14.318) containing indicators from all NRL games during the 2015-2019 seasons (34,047 observations) (see Table 3). The PIs were chosen based on consultation with current NRL coaching staff and were similar to those previously examined and normalised against playing time (Woods et al., 2018b; Woods et al., 2017d). Players were *a priori* classified based on their coach-selected starting line-up and playing number, and then further classified per game into four playing groups (Sirotic et al., 2011). These positional groups have previously been reported to exhibit different physical (Austin et al., 2011; Gabbett et al., 2010, 2012) and technical skill demands (Bennett et al., 2016; Gabbett et al., 2008; Sirotic et al., 2011) in RL athletes (Table 12). Data was collated and then analysed in accordance with approval from the local institutional Human Research Ethics Committee (H7376).

Table 13. Description of *a priori* playing positions.

Position	Position Description
Adjustables	Consists of two halves (five-eighth and halfback), hooker and the fullback. They are the core group of playmakers, responsible for directing the team in general attacking play.
Backs	Consists of the centres and wingers. They form the outermost part of the defensive line. Typically, some of the faster and more athletic players.
Forwards	Consists of the two edge back rowers the middle forwards (prop forwards and lock). They are the bigger players, often relied on for their strong carries in attack and ability to make strong tackles in defence.
Interchange	Typically consists of three bench forwards and a utility player (often a replacement hooker). Similar to the forwards, not required to play periods as long as the starters and relied on for their energy and effort for short periods off the bench.

5.3.1 Statistical Methods

All statistical analyses were carried out using the statistical software IBM SPSS for Windows version 25 (Armonk, NY, USA, IBM Corp.). One-way analysis of variance (ANOVA) was performed to examine changes in the selected technical PIs between 2015 to 2019, for each positional group to identify consistency over time and enable subsequent cluster analysis with differences identified via Bonferroni post-hoc analysis.

Classification of positional groups was achieved via a three-step process: (1) PCA; (2) two-step cluster analysis; and (3) discriminant analysis (Sampaio et al., 2018). PCA is commonly used as a dimension reduction technique that involves reducing the total number of observed variables into 'n' number of factors (Jolliffe, 2011). This is achieved by transforming a set of possibly linear variables into a separate set of linearly uncorrelated variables (principal components; Table 14). These factors were determined using eigenvalues above 1 (Table 15) and further extracted from the rotated component matrix for values above 0.60 (Table 16) (Jolliffe, 2011; Weaving et al., 2019).

Table 14. Principal components and the associated technical performance characteristics.

Factor	Technical Performance Characteristics
Factor 1 (Forward Attacking Play)	runs, run metres, hitups, PTB wins, PTB loss, metres after contact;
Factor 2 (General Play Kicking)	kick total, kick metres, failed kick defusal;
Factor 3 (Kick Pressure)	rambo, tackle made, kick defused;
Factor 4 (Tries)	linebreak, tries, tackle break;
Factor 5 (Kick Breaks)	kick break, kick try assist;
Factor 6 (Conversions)	conversion made, conversion miss, penalty made;
Factor 7 (Penalties)	penalty won, penalty conceded;
Factor 8 (Try Causes)	conceded linebreak, try cause;
Factor 9 (Try Assists)	try assist, linebreak assist;
Factor 10 (Handling Errors)	tackle forced turnover, handling errors;
Factor 11 (Defensive Decisions)	Intercepts, tackle miss;
Factor 12 (Supports)	supports;
Factor 13 (Try Saves)	try saves;
Factor 14 (Botch Try)	botch try;

Table 15. Eigenvalues for principal components and total variance explained.

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	6.585	13.719	13.719	6.585	13.719	13.719	5.001	10.419	10.419
2	3.048	6.350	20.070	3.048	6.350	20.070	3.237	6.743	17.162
3	2.579	5.373	25.442	2.579	5.373	25.442	2.205	4.595	21.757
4	1.959	4.081	29.523	1.959	4.081	29.523	2.009	4.184	25.941
5	1.771	3.689	33.212	1.771	3.689	33.212	1.975	4.114	30.055
6	1.716	3.574	36.787	1.716	3.574	36.787	1.957	4.076	34.132
7	1.598	3.329	40.116	1.598	3.329	40.116	1.943	4.049	38.181
8	1.525	3.177	43.293	1.525	3.177	43.293	1.710	3.563	41.744
9	1.493	3.111	46.404	1.493	3.111	46.404	1.659	3.456	45.200
10	1.330	2.770	49.174	1.330	2.770	49.174	1.590	3.312	48.511
11	1.292	2.692	51.866	1.292	2.692	51.866	1.373	2.859	51.371
12	1.113	2.318	54.184	1.113	2.318	54.184	1.265	2.636	54.007
13	1.068	2.224	56.408	1.068	2.224	56.408	1.130	2.353	56.360
14	1.004	2.092	58.500	1.004	2.092	58.500	1.027	2.140	58.500
15	0.999	2.082	60.582						
16	0.986	2.054	62.636						
17	0.980	2.042	64.678						
18	0.972	2.025	66.703						
19	0.968	2.016	68.718						
20	0.945	1.968	70.687						
21	0.934	1.946	72.632						
22	0.931	1.941	74.573						
23	0.929	1.936	76.508						
24	0.899	1.873	78.382						
25	0.884	1.842	80.224						
26	0.878	1.830	82.053						
27	0.841	1.753	83.806						
28	0.810	1.688	85.494						
29	0.689	1.436	86.930						
30	0.649	1.352	88.283						
31	0.633	1.318	89.600						
32	0.610	1.271	90.872						
33	0.571	1.189	92.061						
34	0.564	1.176	93.237						
35	0.463	0.964	94.200						
36	0.415	0.864	95.064						
37	0.388	0.808	95.871						
38	0.380	0.792	96.663						
39	0.366	0.763	97.426						
40	0.313	0.651	98.077						
41	0.308	0.641	98.719						
42	0.210	0.437	99.156						
43	0.155	0.322	99.478						
44	0.098	0.204	99.682						
45	0.052	0.109	99.792						
46	0.049	0.103	99.895						
47	0.026	0.055	99.950						
48	0.024	0.050	100.000						

Table 16. Rotated component matrix of technical PIs.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Runs	0.956	-0.077	0.039	0.074	-0.028	-0.040	0.012	-0.035	0.038	0.053	-0.006	0.037	0.020	-0.009
Run (m)	0.915	-0.120	0.019	0.168	-0.032	-0.043	0.004	-0.038	0.016	0.019	-0.010	0.031	0.008	-0.007
Line Break	-0.036	-0.014	-0.051	0.882	0.029	0.007	0.006	-0.009	0.039	-0.010	-0.016	0.019	-0.005	0.016
Line Break Ast	-0.085	0.107	-0.043	0.000	-0.018	0.050	-0.002	-0.010	0.905	-0.010	-0.008	0.030	0.017	0.026
Hit Ups	0.773	-0.149	0.454	-0.090	-0.020	-0.060	0.017	-0.043	-0.058	-0.034	0.043	0.074	-0.028	0.003
Kick breaks	-0.046	0.117	-0.016	0.003	0.867	0.042	0.003	0.005	0.035	0.005	0.005	-0.038	0.002	-0.006
Tries	-0.074	-0.030	-0.049	0.853	0.013	0.030	-0.003	-0.011	-0.047	-0.034	-0.007	0.037	-0.009	0.025
Try Ast	-0.118	0.120	-0.063	0.052	0.390	0.062	-0.006	-0.015	0.796	-0.011	-0.009	0.017	0.032	0.040
Offloads	0.310	0.048	0.082	0.054	-0.098	-0.019	0.011	0.026	0.313	0.100	0.062	-0.122	-0.095	-0.120
Tackle Break	0.273	0.002	-0.159	0.627	-0.038	-0.011	0.005	-0.003	0.078	0.083	-0.018	-0.051	0.034	-0.046
Passes	-0.421	0.237	0.262	0.003	0.029	0.030	-0.002	-0.079	0.146	0.044	-0.004	-0.522	0.071	0.057
PTB Win (Attack)	0.698	-0.172	0.129	0.044	-0.033	-0.068	0.004	-0.024	-0.083	-0.022	0.024	0.194	0.016	0.013
PTB Loss (Attack)	0.664	-0.133	-0.133	-0.090	-0.009	-0.018	-0.008	-0.027	-0.059	-0.072	-0.061	-0.109	0.052	-0.008
Tackled FTO	0.052	-0.058	-0.076	0.003	0.014	-0.001	0.010	-0.011	-0.028	0.773	-0.006	0.083	-0.046	0.004
Pass TO	-0.069	0.132	0.045	0.003	-0.011	0.008	0.002	0.024	0.048	0.391	-0.029	-0.191	0.141	-0.003
Botch Try	-0.038	-0.104	-0.015	0.010	0.025	-0.007	-0.006	0.005	-0.011	0.058	-0.005	0.155	-0.009	0.736
Handling Errors	0.003	-0.025	-0.044	0.018	0.004	0.009	0.001	0.015	0.004	0.877	0.051	0.052	-0.029	0.032
Pen Conceded (Atk)	0.015	0.004	0.002	0.004	0.002	0.000	0.984	-0.002	-0.002	0.011	0.071	0.004	0.008	0.003
Pen Won (Atk)	0.016	0.004	0.013	0.004	0.000	0.001	0.985	0.003	0.000	0.005	-0.016	0.004	-0.008	-0.003
Decoy	0.470	-0.148	0.447	-0.098	-0.019	-0.056	0.022	-0.050	-0.044	-0.047	-0.015	0.346	-0.032	0.016
Support	0.070	0.157	-0.034	0.025	-0.018	0.027	0.005	-0.041	0.059	0.023	-0.059	0.794	0.037	0.004
Metres After Contact	0.952	-0.191	0.020	-0.008	-0.048	-0.064	0.009	-0.031	-0.031	0.027	-0.012	0.048	0.017	-0.012
Tackle Made	0.223	-0.119	0.789	-0.178	-0.017	-0.078	0.005	-0.033	-0.064	-0.037	0.004	-0.115	0.021	0.013
Tackle Miss	0.001	0.041	0.192	-0.042	-0.005	0.004	0.023	0.241	0.003	-0.002	0.680	-0.018	0.080	-0.035
Tackle FTO	0.001	0.000	0.122	0.001	-0.007	-0.005	-0.001	-0.049	-0.011	-0.015	0.335	0.070	0.580	0.009

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Scraps	0.066	0.023	-0.043	0.034	0.015	0.009	-0.011	-0.015	0.004	0.046	0.091	-0.095	0.376	0.236
Kick Pressure (Rambo)	0.002	-0.041	0.617	-0.010	-0.014	-0.014	0.010	-0.046	0.007	0.032	-0.071	-0.093	0.020	0.055
Intercepts	-0.032	-0.004	-0.105	0.018	0.015	0.033	-0.014	-0.042	0.004	0.072	0.699	0.045	-0.058	-0.131
Try Saves	-0.021	-0.027	-0.041	-0.021	0.003	0.003	0.011	0.039	0.007	0.004	-0.173	0.029	0.726	-0.149
Pen Conceded (Def)	0.014	-0.006	0.383	0.002	-0.022	0.003	-0.006	0.020	0.010	0.022	-0.061	0.056	0.109	-0.127
Conceded Linebreak	-0.050	-0.004	0.048	-0.016	0.007	-0.010	-0.006	0.907	-0.006	-0.013	0.073	-0.015	-0.019	0.002
Try Cause	-0.082	0.003	-0.126	-0.005	-0.003	-0.005	0.006	0.891	-0.004	0.040	-0.009	-0.008	0.005	0.004
Kick Defused	0.005	-0.018	-0.621	0.072	-0.024	0.016	0.000	-0.002	0.018	0.128	-0.144	0.022	0.196	-0.033
Failed Kick Defusal	-0.124	0.625	-0.023	0.001	0.439	0.106	0.014	0.016	0.030	0.006	0.006	0.071	0.003	0.036
Kick Total	-0.217	0.883	-0.015	-0.005	0.218	0.143	-0.002	0.018	0.074	0.016	-0.016	0.043	0.012	0.070
Kick (m)	-0.209	0.851	0.003	-0.011	0.173	0.144	-0.004	0.018	0.065	0.017	-0.018	0.047	0.006	0.069
FG Made	0.011	0.020	-0.100	-0.021	-0.010	-0.029	0.044	-0.063	0.005	-0.054	0.452	-0.098	0.081	0.192
FG Miss	-0.023	0.246	-0.009	-0.013	-0.008	0.117	-0.012	-0.023	-0.021	0.007	-0.013	0.000	-0.011	-0.106
Pen Made	-0.050	0.116	-0.020	-0.018	-0.031	0.739	-0.003	-0.009	0.006	0.002	-0.008	0.003	0.007	0.052
Pen Miss	-0.018	-0.009	-0.008	0.009	0.087	0.377	-0.011	-0.023	-0.054	0.025	0.035	0.008	-0.023	-0.183
Conversion Made	-0.083	0.176	-0.029	0.026	0.055	0.789	0.006	0.018	0.073	-0.012	-0.017	0.017	0.002	0.067
Conversion Miss	-0.055	0.114	-0.038	0.016	0.014	0.728	0.013	0.010	0.077	-0.007	-0.011	-0.019	0.028	0.073
Kick Try Assist	-0.064	0.177	-0.016	0.003	0.873	0.072	-0.004	-0.003	0.123	0.003	-0.005	-0.005	0.005	0.006
Kick Errors	-0.029	0.308	-0.054	-0.012	-0.019	0.002	0.010	0.000	0.041	-0.005	0.010	-0.088	-0.016	0.131
Kick Forced DO	-0.099	0.598	0.001	0.011	0.028	0.068	-0.017	-0.009	0.053	0.008	-0.033	0.001	0.048	0.021
Kick Dead	-0.058	0.480	-0.043	-0.004	-0.054	-0.010	0.011	-0.002	0.047	-0.006	0.039	-0.050	0.042	0.066
Kick Caught in Goal	-0.038	0.400	-0.012	0.000	0.031	-0.016	0.011	0.014	-0.019	0.005	0.050	0.084	-0.063	-0.102
Kick 40/20	-0.018	0.158	-0.005	-0.008	-0.005	0.016	0.001	0.001	0.006	-0.019	-0.005	-0.102	0.001	0.455

The factors obtained from the PCA were then incorporated into a two-step cluster analysis to model natural positional groups within the dataset. Two-step cluster analysis automatically determines the "optimal" number of clusters (positional groups) by using the Schwartz's Bayesian Information criterion (Wendler & Gröttrup, 2016). In order to determine the "goodness" of the determined solution, the silhouette coefficient was used as a measure to cluster cohesion and separation (Norusis, 2011; Wendler & Gröttrup, 2016). Additionally, the log-likelihood distance measure was used to calculate the similarity between clusters (Wendler & Gröttrup, 2016). Finally, discriminant analysis was used to better differentiate the positional groups determined by the two-step cluster. This approach provides classification functions that best discriminate among clusters (i.e., check which cluster each player best fits) (Jolliffe, 2011). Structure coefficient (SC) values greater than |0.30| were considered significant for identifying the variance of positional technical performance (Zhang et al., 2018).

5.4 Results

The results of one-way ANOVA revealed significant changes in 35 of 48 (73%) technical performance characteristics ($F = 2.3–687.7$; $p = 0-0.05$; partial $\eta 2 = 0.00–0.075$) across the chosen time-period (2015-2019 NRL seasons). The performance characteristics which differed across seasons were: runs, run metres, line break, line break assist, hit ups, kick breaks, try assist, tackle break, PTB win, PTB loss, botch try, handling errors, penalty conceded, penalty won, decoy, support, metres after contact, tackle made, tackle miss, tackle forced turnover, scarps, kick pressure, intercepts, try saves, penalty conceded (def), conceded line break, try cause failed kick defusal, kick metres, field goal made, field goal miss, penalty made, kick errors, kick dead, kick caught in goal. Principal component analysis revealed fourteen factors (principal components, Table 17) that explained the variance of different performance outcomes based on the PIs. Factor 1 (forward attacking play) explained 13.7% of the total variance, while factor 2 (general play kicking) accounted for 6.4% and factor 3 (kick pressure) explained 5.4%. The cumulative loading for all fourteen factors accounted for 58.5% of the variance of positional technical performance across the competition.

Table 17. Principal components and the associated technical performance characteristics.

Factor	Technical Performance Characteristics
Factor 1 (Forward Attacking Play)	runs, run metres, hitups, PTB wins, PTB loss, metres after contact;
Factor 2 (General Play Kicking)	kick total, kick metres, failed kick defusal;
Factor 3 (Kick Pressure)	rambo, tackle made, kick defused;
Factor 4 (Tries)	linebreak, tries, tackle break;
Factor 5 (Kick Breaks)	kick break, kick try assist;
Factor 6 (Conversions)	conversion made, conversion miss, penalty made;
Factor 7 (Penalties)	penalty won, penalty conceded;
Factor 8 (Try Causes)	conceded linebreak, try cause;
Factor 9 (Try Assists)	try assist, linebreak assist;
Factor 10 (Handling Errors)	tackle forced turnover, handling errors;
Factor 11 (Defensive Decisions)	Intercepts, tackle miss;
Factor 12 (Supports)	supports;
Factor 13 (Try Saves)	try saves;
Factor 14 (Botch Try)	botch try;

The two-step cluster analysis (Figure 5) achieved a good silhouette measure of cohesion and separation (average silhouette = 0.5) revealing six clusters as opposed to the four *a priori* positional classifications. The clusters were: cluster 1 'backs' (20.9% of all players; 100% accuracy); cluster 4 'adjustables' (17.2% of all players; 100% accuracy); cluster 3 'interchange' (23.2% of all players; 99.9% accuracy); and cluster 6 'forwards' (26.7% of all players; 100% accuracy). The two additional clusters which were identified were cluster 2 labelled as 'utility back' (6.5% of all players) which consisted of a combination of two *a priori* classified groups, 'adjustables' (74.7%) and 'backs' (17.3%) players; and cluster 3 labelled as 'interchange forwards' (5.5% of all players) consisting of a combination of 'interchange' (50.8%) and 'forwards' (30%).

The discriminant analysis revealed that 62.9% of the originally grouped clusters (i.e. two-step clustering) were correctly classified using the 14 factors obtained via PCA. The greatest level of classification accuracy occurred in cluster 1 (backs; 93.2%), followed by cluster 2 (utility back; 84.2%), cluster 3 (interchange forwards; 65.5%), cluster 4 (adjustables; 64.1%), cluster 6 (forwards; 50.4%, interchange; 37.7%) and cluster 5 (interchange; 42.3%, forwards; 41.6%). The discriminant analysis identified five significant discriminant functions (accounting for variance of kick conversions, general attacking play, penalties, general play kicking and scoring attacking play, respectively). The significant factors were forward attacking play (functions 2 and 5: SC=0.39 and SC=-0.34, respectively), general play kicking (function 4: SC=-0.63), kick pressure (function 4: SC=-0.51), conversions (function 1: SC=0.44), penalties (function 3: SC=-0.51), try causes (function 5: SC=-0.33), try assists (function 5: SC=0.38) and supports (function 5: SC=0.63).

Clusters

Input (Predictor) Importance

1.0 0.8 0.6 0.4 0.2 0.0

Cluster	6	5	1	4	2	3
Label	Forwards	Interchange	Backs	Adjustables	Utility Back	Interchange Forwards
Description						
Size	26.7% (9099)	23.2% (7889)	20.9% (7115)	17.2% (5841)	6.5% (2216)	5.5% (1866)
Inputs	Conversions -0.12	Conversions -0.12	Conversions -0.16	Conversions -0.31	Conversions 2.37	Conversions -0.14
	Defensive Decisions -0.01	Defensive Decisions -0.03	Defensive Decisions -0.03	Defensive Decisions -0.17	Defensive Decisions -0.05	Defensive Decisions 0.91
	Forward Attacking Play 0.37	Forward Attacking Play 0.43	Forward Attacking Play -0.33	Forward Attacking Play -0.69	Forward Attacking Play -0.42	Forward Attacking Play 0.30
	General Play Kicking -0.27	General Play Kicking -0.20	General Play Kicking -0.36	General Play Kicking 0.74	General Play Kicking 1.19	General Play Kicking -0.22
	Kick Breaks -0.05	Kick Breaks -0.05	Kick Breaks -0.09	Kick Breaks -0.28	Kick Breaks 1.49	Kick Breaks -0.10
	Kick Pressure 0.48	Kick Pressure 0.46	Kick Pressure -0.99	Kick Pressure -0.21	Kick Pressure -0.16	Kick Pressure 0.33
	Penalties -0.15	Penalties -0.15	Penalties -0.08	Penalties -0.10	Penalties 0.01	Penalties 1.93
	Playing Position Forwards (100.0%)	Playing Position Interchange (99.9%)	Playing Position Backs (100.0%)	Playing Position Adjustables (100.0%)	Playing Position Adjustables (74.7%)	Playing Position Interchange (50.8%)
	Tries -0.16	Tries -0.26	Tries 0.24	Tries 0.03	Tries 0.03	Tries 0.82
	Try Assists -0.11	Try Assists -0.21	Try Assists -0.12	Try Assists 0.26	Try Assists 0.34	Try Assists 0.69
	Try Saves -0.12	Try Saves -0.12	Try Saves -0.12	Try Saves 0.20	Try Saves 0.00	Try Saves 0.92
	Botch Try -0.03	Botch Try 0.00	Botch Try -0.12	Botch Try -0.06	Botch Try 0.66	Botch Try -0.01
	Supports 0.15	Supports -0.00	Supports 0.03	Supports -0.29	Supports 0.01	Supports 0.03
	Handling Errors -0.12	Handling Errors -0.06	Handling Errors 0.02	Handling Errors 0.13	Handling Errors 0.01	Handling Errors 0.36
	Try Causes -0.06	Try Causes 0.01	Try Causes 0.13	Try Causes -0.07	Try Causes 0.00	Try Causes -0.05

Figure 5. Two-Step Cluster analysis results identifying six distinct playing position clusters.

5.5 Discussion

This chapter investigated whether there have been any changes over seasons in the technical PIs of different positional groups in the NRL, and whether these positional groups could be classified and discriminated based on PIs. The results identified significant changes in the PIs over the selected time-period with 27% of indicators (e.g., tries, kick defused, conversion made/miss, kick 40/20) stable across the 2015-2019 NRL seasons. Further, a model was created, which accurately classified playing position based upon a series of factors derived from commonly used PIs (Sampaio et al., 2018; Zhang et al., 2018). Collectively, these findings identified a newly developed model confirming the efficacy of unsupervised classification analysis for positional technical performance in RL. As such, with the large amount of data available to sports teams, the use of an unsupervised classification approach such as PCA, sports practitioners will be able to refine the vast amount of data available to them, into information that they may find more useful. Subsequently, the positional classification characteristics identified in this chapter may also allow sports practitioners to better prepare current players for their specified role, manage recruitment, and potentially identify new positions better suited for current players.

A major finding of this chapter was the observed variation in technical performance characteristics over the chosen time-period (2015-2019). This finding is supported by previous research which had observed changes in league-wide technical performance over 11 seasons (2005-2016)(Woods et al., 2018b). The authors suggested that the introduction of a series of new rules by the NRL prior to the commencement of the 2016 NRL season, namely the reduction in interchanges (from 10 to 8) and the introduction of a 'shot clock' (35 seconds for scrums and 30 seconds for dropouts) may have augmented the subsequent outputs of players (Woods et al., 2018b). Potentially, the individual playing style of teams and how playing positions were utilised within that style, rather than the specific role of each playing position, may have contributed to the contrasting different result (Sirotic et al., 2011; Woods et al., 2018a; Woods et al., 2018b). Regardless, it is evident that the technical performance demands in the NRL is constantly evolving, which has been further supported by the results of this chapter. As such, it is important that teams are constantly monitoring these changes, such that coaching staff can make informed decisions regarding training and strategizing game tactics.

The model produced in this chapter was successful in identifying six positional clusters, with a good level of accuracy (i.e., successfully assigning 89.4% of the players to their *a priori* cluster). This result highlights the suitability of clustering analysis to assist performance staff with accurate classification of RL playing positions using competition performance. As such, this approach may be further applied to talent identification or recruitment strategies, as it may identify players in other competitions (e.g., Super League, Reserve Grade, U20s) through comparisons of their performance against other players in the NRL (and possibly their most suited position). Combining match technical performance characteristics with other important physical measures could form part of a robust talent identification tool (Pion et al., 2015).

Another intriguing result from the cluster analysis was the identification of two additional clusters. The first additional cluster (cluster 2) consisted of a combination of adjustables (74.7%) and backs (17.3%), who exhibited a unique set of technical performance characteristics which have been labelled as a ‘utility back’ group. The main features of this group were kicking (including goal kicking and kick breaks), try assists, intercepts, try causes and botched tries. The other additional positional cluster (cluster 3) consisted primarily of a combination of interchange (50.8%) and forward players (30%), which have subsequently been labelled as ‘interchange forwards’. The main features of this ‘interchange forwards’ group were forward attacking play, defensive decisions, penalties, kick pressure, try assists, try saves and handling errors. Discriminant analysis further revealed that 84.2% of players classified as a 'utility back' would have been reclassified in the same cluster and 65.5% 'interchange forwards' reclassified in the same cluster with the remainder primarily reclassified amongst adjustables (9.5%) and forwards (13.5%). One of the most representative examples of the 'utility back' playing group was Player X who would traditionally be considered a 'fullback' (adjustable) but was re-classified as 'utility back' for 36% of matches and an 'adjustable' for 64% of 112 matches. Whereas one of the more representative examples of the 'Interchange Forward' group was Player Y (47 % of 98 matches as 'Interchange Forward', 22% as 'Interchange' and 31% as 'Forward'). It is however unclear whether one or both of these additional positional groups were commonly featured amongst all teams, or whether successful (or unsuccessful) teams consisted of these types of players. As such, further investigation into the influence of this positional group on match outcome may be of value to coaching and performance staff regarding tactical game planning and player development and recruitment strategies.

Discriminant analysis revealed the difficulty of reclassifying 'interchange' players into the same cluster, with 42.3% of interchange players successfully reclassified in cluster 5, and 41.6% assigned to cluster 6 (forwards). Given it is common practice for NRL teams to assign multiple (often three out of four) spots on their interchange towards forward-positional players, it is unsurprising that there was a level of misclassification that occurred during this analysis process. Given this, it could be assumed that 'interchange' players were expected to be able to make similar performance contributions to the team as 'forwards'. An example of this would be Player Z (97.1% of 110 matches as 'Forward'; 2.9% of matches as 'Interchange'), who was traditionally considered a 'Interchange Forward' compared to Player Y (47 % of 98 matches as ‘Forward’, 22% as ‘Interchange’ and 31% as ‘Forward’) who would also be considered a ‘Forward’. Both of these players would be considered to be within the ‘Forward’ group, as classified *a priori* however, the individual match performance of Player Z was variable compared to that of a ‘Forward’ and fluctuated between a starting and reserve role. As such, coaches should ensure any positional specific training that is planned, gives similar opportunity to players that undertake similar roles irrespective of start position (field or bench).

The current chapter highlighted the efficacy of unsupervised classification for positional technical performance in RL over recent seasons through the use of PCA, two-step clustering and discriminant analysis. However, in contrast to previous research, this chapter only sampled five seasons worth of data compared to previous research which observed changes over 11 seasons (Woods et al., 2018b). In saying this, changes noted in this chapter are similar to prior research (Woods et al., 2018b), confirming that the NRL is evolving and that larger observational periods may be required to gain a deeper insight into the evolution of playing position in the NRL. Additionally, it is important to note that the *a priori* classification of NRL playing positions was determined by how players were initially listed when their teams were announced prior to the game. As such, players named outside of the 17 initially intended to be playing, were assigned numbers beyond 17 (e.g., 18, 19, 20, etc.). For example, a player who was replaced from outside the original 17 at late notice due to injury (e.g., back) was unable to be differentiated from the interchange group, and as such may have resulted in some initial *a priori* misclassification. However, the unsupervised approaches used in this chapter overcome this issue, as the analysis determines which positional group each player falls into, rather than coaches.

5.6 Conclusions & Practical Implications

This chapter identified changes in the technical performance demands of NRL players across the sampled seasons in the NRL (2015-2019). The current chapter also demonstrated the usefulness of both clustering (two-step) and classification (discriminant analysis) approaches to understanding the positional technical performance characteristics of NRL players. The high level of classification accuracy achieved from these approaches indicated that the chosen analytical techniques could be used to support sports practitioners in their evaluation of player performance and future positional suitability (e.g., talent identification, personnel recruitment). More importantly, this chapter highlighted the utility of unsupervised analytical approaches for sports practitioners, as they can offer insights into queries that they may not be able to resolve using traditional analytical approaches.

Further application of the results of this chapter could assist sports practitioners in providing greater decisional support with the design and implementation of various training and game-play strategies. In order to do this however, it is important to gain a greater understanding of the relative contribution(s) to team performance (and subsequent success) that each of the identified positional groups. In addition to this, further exploration into the addition of other technical, tactical and contextual information (e.g., match location) may augment the way various positional groups are utilised to fit different match-contexts and their subsequent contributions to match success. For example, given the current emphasis on increasing attacking PTB wins (Chapter 2), is the emphasis on this area of the game increased (or decreased) depending on match location (i.e., Home or Away)? In this instance, the tactical game-planning required by coaches as the home (or away) team might involve spotting up opposition middle (ruck) defenders to tire them out quicker and therefore generate faster PTB speeds. Continuing examination of teams' styles of play, and the impact of contextual factors on these styles, will enable greater decision making for coaching and performance staff for future success.

5.7 Key Points

- PCA is a useful model to associate and group PIs into factors that may explain RL player´s performances.
- Clustering techniques (e.g. two-step cluster) using unsupervised approaches allow analysts to classify player´s performance into different profiles that account for related PIs and roles during competition.
- The identification of specific playing positions and the discrimination among them via performance factors may enable establishment of player's performance profiles, critiquing of player´s performances over seasons and identify player´s recruitment potential and suitability.
- Further application of the results of this chapter could assist sports practitioners in providing greater decisional support with the design and implementation of various training and game-play strategies

CHAPTER 6: Effect of match factors on positional performance in the National Rugby League

Publication

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Author Contributions

C.J.W. contributed 75% to this chapter. He developed the chapter structure, wrote each section, collated and analysed the data. C.T.W, M.A,G and A.S.L offered conceptual guidance and statistical support where required (15%), while W.H.S contributed to the manuscript drafting and construction of ideas within the discussion (10%).

6.1 Abstract

Objectives: To examine the effects of match-related contextual variables on positional groups and success in the National Rugby League (NRL). **Methods:** Data relating to match location, match outcome, quality of opposition and match type (absolute score differential) from all matches across the 2015-2019 NRL seasons were collected, in addition to 14 previously identified Factors (technical PIs). A decision tree, grown using the Exhaustive Chi-square Automatic Interaction Detector (CHAID) algorithm, was used to model the effect of each of these match-related contexts on positional contribution according to match outcome. **Results:** The accuracy of the exhaustive CHAID model in explaining the influence of positional groups on match outcome was 66%. The model revealed four primary splits: interchange forwards, utility backs, adjustables and a group containing the remaining three positional groups (forwards, backs, and interchange). **Conclusions:** Results suggest that interchange forwards, utility backs and adjustables could have a definitive role within the team compared to the remaining positional groups in determining match outcome. In contrast to team-level research, there is a greater emphasis on the importance of defensive actions (e.g. try causes, tackles made) at a positional level then attacking PIs. The moderate classification accuracy justifies the use of this approach for examination of the interactions between match-related contextual variables, PIs and positional groups.

6.2 Introduction

The capture and analysis of technical PI in team-sports has been widely investigated (Lord et al., 2020a, 2020b), with these works adding value to the understanding of competition trends and to support decision making. For example, research in Australian Football (Greenham et al., 2017; Woods et al., 2018c; Woods et al., 2017e), basketball (Jaime Sampaio et al., 2010; Zhang et al., 2017; Zhang et al., 2018) and soccer (Aguado-Méndez et al., 2020; Bush et al., 2015) has identified various PIs, such as number (or type) of passes, scoring opportunities, tackles made, score assists and errors, that differentiate positional groups and supports the development of training and match-strategies important for success.

In Rugby League, similar research has examined the various positional requirements of players during game play (Bennett et al., 2016; Chapter 5; Sirotic et al., 2011). This work has identified that forwards, hookers, and halves complete more tackles per minute than backs (and full backs), while forwards complete a greater number of offensive and defensive actions compared to backs and adjustables (halves, hooker and fullback) (Bennett et al., 2016; Sirotic et al., 2011). More recently, Wedding et al. (2020) identified two additional positional groups (interchange forwards and utility backs) using an unsupervised classification technique (two-step clustering) – complementing the four *a priori* positional groups of adjustables, backs, forwards, and interchange – supporting the design of positionally-focused practice designs in Rugby League. Whilst such work has been important for understanding differences between playing positions, research is yet to explore how these positional groups change their contribution to match success based on match-related contextual factors.

Several studies in team sports have explored the effects of match-related contextual variables, such as *match location* (Almeida et al., 2014; Courneya & Carron, 1992; Gomez et al., 2008), *quality of opposition* (Almeida et al., 2014; Woods et al., 2017d) and *score differential* (match type) (Sampaio & Janeira, 2017; J. Sampaio et al., 2010; Teramoto & Cross, 2010) on match outcome. These match considerations have enabled performance analysts (and subsequently coaching staff), to better understand successful team performance across a range of contexts. Notably, the PIs important for distinguishing the characteristics of positional groups across a range of match-contexts in soccer were recently examined (Yi et al., 2020). The authors reported that the quality of opposition, match outcome and quality of opponent produced the strongest effects on players' performances, highlighting the need for further consideration of these match contexts when examining or evaluating player performance (Yi et al., 2020). Whilst similar research has been conducted in Rugby League (Chapter 4; Parmar et al., 2018b), the influence of different match-contexts, and the subsequent impact on positional groups' performance and match outcome, have yet to be determined. The aim of this chapter was to examine the effects of different match-related contexts and positional groups on match outcome in the National Rugby League (NRL).

6.3 Methods

Data was collated from a licensed central database (Analyzer; The League Analyst, Version V4.14.318) and consisted of 1,005 matches across five seasons in the NRL (2015-2019). By focusing on this 5-year sample, the current chapter was able to build on work, in which technical PIs (Fernandez-Navarro et al., 2016; Parmar et al., 2018a; Wedding et al., 2021a) and positional groups (Chapter 5; Zhang et al., 2018) have previously been identified via unsupervised clustering techniques. Additionally, the significant impact of COVID-19 and rule changes during the 2020 NRL season rendered the data for that season too heterogeneous for inclusion.

Guided by the results of Chapter 5, I classified technical PIs into 14 Factors (via a data reduction method – principal component analysis, PCA), which could then be used to best describe the technical characteristics of positional performance (Table 2). Positional groups utilised for this chapter were previously identified via unsupervised classification and were categorised as backs, forwards (middle and edge forwards), interchange forwards, adjustables (halves, fullback and hooker), interchange, and utility backs (see, Chapter 5 for further insights). Further, the addition of match-related contextual variables of included below were guided by similar studies in RL (Chapter 4; Parmar et al., 2018a):

- *Match location* (Home / Away / Neutral),
- *Match type* (absolute score margin calculated as |team score – opposition score|),
- *Quality of opposition* (end of season ladder position)

Match outcome was coded for Wins and Losses, with matches ending in a draw (n = 4) omitted from analyses. *Quality of opposition* was defined by whether teams reached the finals (i.e., finished the season in the 'top eight') in that respective season (Lago, 2009). For example, if a team that made the finals played a team that did not, then the quality of opposition was defined as 'worse'. Similarly, for a match where both teams did not make finals that season, the quality of opposition for both teams was considered as 'balanced'. All data was collated and analysed in accordance with approval from the local Human Research Ethics Committee (H7376).

6.3.1 Statistical Analyses

Data was modelled using two-step cluster analysis followed by classification and decision trees, grown using the exhaustive Chi-square automatic interaction detection (CHAID) algorithm. Two-step cluster analysis was used to identify different match types, with the 'optimal' number of clusters determined via the Schwartz's Bayesian Information Criterion (Chapter 4; Wendler & Gröttrup, 2016). Given the nature of the other response variables, cluster analysis was not required prior to further analysis. The Silhouette coefficient (≥ 0.7) was used to measure cluster cohesion and separation in order to determine the "goodness" of the clustering (Norusis, 2011; Wendler & Gröttrup, 2016). Further, similarity between clusters was calculated using log-likelihood distance measures (Norusis, 2011).

Exhaustive CHAID was used to identify how the performance of positional groups effected match outcome, using various response variables (i.e., *match location*, *match type* and *quality of opposition*) and previously identified Factors (Cui et al., 2019). Match outcome was the dependent variable with the first categorisation/split forced for playing position(s) to enable subsequent CHAID results to clarify how winning and losing could be influenced by positional groups. The following criteria assisted the build of the model: (i) maximum number of iterations was 100, (ii) statistical significance was set to $p < 0.05$, (iii) Pearson's Chi-square values were used to detect the relationship(s) between independent variables, (iv) the minimum change in expected cell frequencies was 0.001, and (v) the Bonferroni method was used for significant value adjustments (Cui et al., 2019). Additionally, the risk of misclassification was calculated as a measure of the reliability of the model using cross-validation of 10 training splits (Cui et al., 2019; Schnell et al., 2014).

6.4 Results

Two-step cluster analysis identified four different *match types* (average silhouette coefficient = 0.7) as follows: 'Close' (34.8% of all matches, absolute points margin = 3.2), 'Balanced (34.4%, absolute points margin = 11.5), 'Unbalanced' (22%, absolute points margin = 22.6) and 'Runaway' matches (8.8%, absolute points margin = 35.6).

Descriptive statistics were compiled for each position group per each response variable (Tables 18-21). Exhaustive CHAID revealed an average 66% classification accuracy for *match outcome* using positional group performance (i.e., wins were classified at 71.7% and losses at 60.3%). The independent variables included in the model were: positional groups, *quality of opposition*, *match type*, try causes, defensive decisions, handling errors and *match location*. The model grew a total of 58 nodes (41 terminal nodes), which given the size of the tree, was split into four separate trees beginning with the first positional group split (or combined positional groups). For example, Figure 6 (Node 1, playing position = forwards, interchange and backs) was the only tree split that featured more than one positional group as part of the first partition. Node 1 was then split by *quality of opposition*, where the likelihood of winning against 'Better' opposition was 25.1% (Node 5), compared to 48.8% (Node 6) and 74.6% (Node 7) when competing against 'Balanced' and 'Worse' opposition, respectively. Continuing from Node 7 (*quality of opposition* = 'Worse'), the tree was then split by *match type* with the greatest likelihood of winning (92.9%) occurring in Node 27 (*match type* = 'Runaway'), and the lowest at Node 28 (66.3%; *match type* = 'close').

Table 18. Descriptive statistics for position and match type.

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forward Attacking Play	Close	0.42	0.91	0.17	1.37	0.48	1.17	0.27	1.10	-0.61	0.71	-0.31	0.52
	Balanced	0.38	0.91	0.35	1.59	0.43	1.17	0.28	1.09	-0.62	0.70	-0.32	0.50
	Unbalanced	0.31	0.90	0.18	1.32	0.41	1.19	0.16	1.02	-0.64	0.69	-0.35	0.51
	Runaway	0.31	0.93	0.50	2.58	0.36	1.13	0.16	1.10	-0.69	0.65	-0.40	0.50
General Play Kicking	Close	-0.26	0.26	0.18	1.53	-0.19	0.39	-0.23	0.49	0.99	1.73	-0.35	0.29
	Balanced	-0.26	0.29	0.29	1.60	-0.19	0.38	-0.23	0.53	0.86	1.64	-0.36	0.28
	Unbalanced	-0.28	0.27	0.08	1.70	-0.20	0.38	-0.23	0.60	0.75	1.52	-0.38	0.27
	Runaway	-0.27	0.30	0.24	2.46	-0.21	0.39	-0.31	0.43	0.67	1.51	-0.40	0.26
Kick Pressure	Close	0.51	0.59	0.33	1.61	0.48	0.90	0.41	1.02	-0.18	1.09	-1.00	0.55
	Balanced	0.49	0.57	0.09	1.41	0.44	0.86	0.34	1.02	-0.21	1.06	-0.99	0.53
	Unbalanced	0.47	0.58	0.35	1.25	0.38	0.83	0.36	0.97	-0.20	1.01	-0.98	0.52
	Runaway	0.41	0.58	0.30	1.31	0.34	0.75	0.29	0.92	-0.17	1.01	-0.95	0.55
Tries	Close	-0.17	0.72	0.48	2.42	-0.31	0.52	0.30	1.39	-0.03	0.76	0.20	0.94
	Balanced	-0.15	0.77	0.42	1.93	-0.28	0.54	0.29	1.41	0.02	0.81	0.25	0.97
	Unbalanced	-0.14	0.80	1.25	4.16	-0.29	0.55	0.33	1.45	0.08	0.88	0.27	1.05
	Runaway	-0.13	0.84	1.51	2.94	-0.24	0.65	0.47	1.60	0.13	0.98	0.39	1.21
Kick Breaks	Close	-0.05	0.19	0.41	2.38	-0.04	0.21	-0.10	0.35	0.04	1.50	-0.09	0.32
	Balanced	-0.05	0.23	0.42	2.20	-0.05	0.21	-0.11	0.37	0.14	1.63	-0.09	0.34
	Unbalanced	-0.05	0.23	0.99	5.34	-0.05	0.21	-0.10	0.41	0.25	1.85	-0.07	0.36
	Runaway	-0.05	0.27	1.16	3.68	-0.04	0.25	-0.11	0.36	0.24	1.85	-0.09	0.28
Conversions	Close	-0.11	0.20	0.09	1.28	-0.12	0.17	-0.12	0.42	0.41	1.81	-0.15	0.41
	Balanced	-0.11	0.26	0.09	1.38	-0.13	0.15	-0.15	0.31	0.39	1.86	-0.16	0.38
	Unbalanced	-0.11	0.22	0.12	1.54	-0.12	0.19	-0.14	0.39	0.42	2.02	-0.16	0.32
	Runaway	-0.13	0.13	0.05	1.80	-0.13	0.13	-0.17	0.29	0.49	2.29	-0.17	0.28
Penalties	Close	-0.15	0.03	0.04	0.99	-0.15	0.04	1.76	3.24	-0.08	0.41	-0.13	0.13
	Balanced	-0.15	0.03	-0.01	0.84	-0.15	0.04	1.54	3.14	-0.07	0.44	-0.13	0.06
	Unbalanced	-0.15	0.03	-0.20	0.14	-0.15	0.03	1.66	3.30	-0.09	0.38	-0.13	0.03
	Runaway	-0.14	0.03	-0.09	0.91	-0.15	0.04	1.32	3.33	-0.07	0.43	-0.13	0.03

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Try Causes	Close	-0.12	0.75	-0.08	1.22	-0.30	0.63	0.66	1.83	-0.12	0.76	0.04	0.83
	Balanced	-0.07	0.81	0.04	1.59	-0.28	0.66	0.93	2.09	-0.06	0.79	0.09	0.87
	Unbalanced	-0.05	0.83	0.05	1.33	-0.26	0.70	0.91	1.88	-0.02	0.83	0.20	1.00
	Runaway	0.06	0.96	0.01	1.15	-0.18	0.78	1.27	2.25	0.10	1.02	0.41	1.26
Try Assists	Close	-0.13	0.59	-0.13	1.15	-0.24	0.37	0.51	1.87	0.18	1.21	-0.14	0.70
	Balanced	-0.11	0.63	-0.10	1.07	-0.24	0.35	0.51	1.81	0.25	1.23	-0.10	0.75
	Unbalanced	-0.11	0.63	-0.09	1.05	-0.25	0.35	0.61	2.19	0.41	1.35	-0.11	0.74
	Runaway	-0.05	0.75	0.29	1.95	-0.23	0.35	0.75	2.31	0.61	1.63	-0.10	0.76
Handling Errors	Close	-0.13	0.75	1.01	3.17	-0.25	0.65	0.54	1.58	0.11	0.78	0.01	0.76
	Balanced	-0.12	0.78	0.78	3.55	-0.25	0.63	0.48	1.53	0.09	0.78	0.05	0.80
	Unbalanced	-0.14	0.76	1.09	2.56	-0.27	0.62	0.51	1.63	0.09	0.81	0.03	0.82
	Runaway	-0.16	0.77	0.23	1.65	-0.29	0.61	0.36	1.47	0.07	0.84	-0.02	0.73
Defensive Decisions	Close	-0.01	0.55	2.34	5.19	-0.06	0.57	0.02	0.68	-0.16	0.56	-0.03	0.59
	Balanced	-0.01	0.52	2.35	5.25	-0.04	0.58	-0.02	0.61	-0.14	0.55	-0.02	0.61
	Unbalanced	0.00	0.54	0.63	2.51	-0.04	0.55	-0.01	0.62	-0.13	0.58	-0.01	0.62
	Runaway	-0.05	0.48	0.41	2.05	-0.03	0.61	0.04	0.71	-0.13	0.60	-0.02	0.60
Supports	Close	0.15	0.75	-0.12	2.01	0.03	1.08	0.02	1.07	-0.20	1.30	0.03	0.55
	Balanced	0.16	0.74	-0.32	1.90	0.01	1.11	-0.02	1.05	-0.21	1.22	0.04	0.54
	Unbalanced	0.17	0.73	-0.09	1.74	-0.02	1.05	0.01	1.05	-0.21	1.23	0.03	0.55
	Runaway	0.09	0.76	0.39	3.01	-0.01	0.96	-0.05	0.99	-0.21	1.24	0.02	0.54
Try Saves	Close	-0.08	0.76	1.77	3.12	-0.08	0.80	-0.15	0.77	0.14	0.89	-0.12	0.71
	Balanced	-0.11	0.75	1.95	3.58	-0.10	0.79	-0.16	0.80	0.17	0.89	-0.11	0.73
	Unbalanced	-0.10	0.76	1.63	3.19	-0.10	0.78	-0.18	0.75	0.15	0.91	-0.12	0.75
	Runaway	-0.17	0.73	1.20	2.66	-0.10	0.82	-0.21	0.80	0.13	0.89	-0.14	0.72
Botch Try	Close	-0.02	0.32	1.25	4.39	0.00	0.36	-0.04	0.39	-0.11	0.70	-0.13	0.28
	Balanced	-0.03	0.31	1.70	4.55	0.00	0.38	-0.01	0.40	-0.02	0.55	-0.12	0.28
	Unbalanced	-0.04	0.33	1.70	4.54	0.01	0.38	-0.02	0.38	0.01	0.51	-0.12	0.29
	Runaway	-0.03	0.29	3.02	11.85	-0.05	0.37	-0.02	0.39	0.04	0.49	-0.10	0.28

Table 19. Descriptive statistics for position and match outcome.

Factor	Match Outcome	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forward Attacking Play	Win	0.48	0.96	0.35	1.62	0.55	1.22	0.35	1.12	-0.60	0.70	-0.33	0.52
	Loss	0.27	0.85	0.10	1.39	0.32	1.11	0.15	1.04	-0.66	0.69	-0.33	0.49
General Play Kicking	Win	-0.24	0.29	0.15	1.56	-0.18	0.37	-0.24	0.47	0.81	1.63	-0.37	0.28
	Loss	-0.29	0.26	0.26	1.86	-0.21	0.39	-0.23	0.57	0.92	1.64	-0.36	0.28
Kick Pressure	Win	0.41	0.58	0.18	1.53	0.36	0.87	0.37	0.95	-0.19	1.04	-0.98	0.53
	Loss	0.56	0.57	0.38	1.29	0.50	0.85	0.36	1.04	-0.20	1.07	-1.00	0.54
Tries	Win	-0.07	0.87	0.77	2.43	-0.25	0.58	0.60	1.63	0.14	0.91	0.43	1.12
	Loss	-0.24	0.65	0.59	3.49	-0.33	0.50	0.10	1.21	-0.09	0.70	0.07	0.84
Kick Breaks	Win	-0.05	0.22	0.65	3.79	-0.04	0.22	-0.09	0.38	0.25	1.88	-0.07	0.36
	Loss	-0.05	0.22	0.53	2.31	-0.05	0.20	-0.12	0.36	0.03	1.38	-0.10	0.30
Conversions	Win	-0.11	0.22	0.11	1.47	-0.12	0.16	-0.16	0.30	0.70	2.31	-0.17	0.34
	Loss	-0.11	0.23	0.06	1.31	-0.12	0.17	-0.12	0.41	0.11	1.34	-0.14	0.40
Penalties	Win	-0.15	0.03	0.00	0.89	-0.15	0.04	1.64	3.40	-0.09	0.39	-0.13	0.11
	Loss	-0.14	0.03	-0.11	0.66	-0.14	0.03	1.60	3.10	-0.07	0.44	-0.13	0.06
Try Causes	Win	-0.21	0.69	-0.08	1.41	-0.36	0.59	0.42	1.71	-0.24	0.66	-0.11	0.75
	Loss	0.06	0.89	0.14	1.33	-0.20	0.73	1.25	2.12	0.14	0.91	0.35	1.03
Try Assists	Win	-0.08	0.69	0.03	1.23	-0.23	0.39	0.78	2.21	0.51	1.45	-0.09	0.79
	Loss	-0.15	0.55	-0.31	1.01	-0.26	0.33	0.38	1.75	0.06	1.07	-0.14	0.67
Handling Errors	Win	-0.17	0.75	0.64	2.89	-0.29	0.61	0.42	1.54	0.03	0.75	-0.04	0.75
	Loss	-0.10	0.77	1.41	3.46	-0.23	0.65	0.56	1.58	0.17	0.82	0.09	0.81
Defensive Decisions	Win	-0.02	0.51	2.65	5.35	-0.06	0.57	0.02	0.66	-0.15	0.57	-0.03	0.59
	Loss	0.00	0.55	0.36	2.34	-0.03	0.58	-0.01	0.64	-0.14	0.56	-0.02	0.62
Supports	Win	0.16	0.76	-0.22	1.92	0.03	1.10	0.08	1.10	-0.13	1.31	0.06	0.55
	Loss	0.15	0.72	0.01	2.12	-0.01	1.05	-0.07	1.00	-0.28	1.18	0.01	0.54
Try Saves	Win	-0.07	0.75	1.69	3.00	-0.07	0.80	-0.12	0.79	0.19	0.91	-0.08	0.74
	Loss	-0.13	0.75	1.87	3.73	-0.12	0.77	-0.21	0.77	0.12	0.87	-0.16	0.71
Botch Try	Win	-0.02	0.32	1.59	4.52	0.01	0.38	0.00	0.41	0.00	0.63	-0.11	0.28
	Loss	-0.04	0.32	1.73	6.53	-0.01	0.37	-0.04	0.38	-0.08	0.55	-0.13	0.28

Table 20. Descriptive statistics for position and match type.

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forward Attacking Play	Better	0.30	0.90	0.26	1.44	0.33	1.14	0.13	1.03	-0.65	0.68	-0.30	0.51
	Balanced	0.37	0.90	0.21	1.46	0.47	1.19	0.25	1.11	-0.62	0.70	-0.33	0.50
	Worse	0.45	0.93	0.34	1.80	0.48	1.16	0.32	1.06	-0.63	0.71	-0.36	0.52
General Play Kicking	Better	-0.28	0.26	0.09	1.39	-0.21	0.38	-0.24	0.54	0.88	1.66	-0.36	0.27
	Balanced	-0.26	0.28	0.24	1.78	-0.18	0.40	-0.24	0.51	0.89	1.65	-0.36	0.29
	Worse	-0.25	0.29	0.23	1.73	-0.20	0.35	-0.24	0.53	0.81	1.59	-0.37	0.27
Kick Pressure	Better	0.54	0.58	0.08	1.43	0.44	0.86	0.31	1.02	-0.21	1.03	-0.98	0.54
	Balanced	0.48	0.57	0.28	1.46	0.45	0.86	0.38	1.01	-0.20	1.06	-1.00	0.54
	Worse	0.43	0.59	0.37	1.45	0.39	0.86	0.40	0.94	-0.17	1.06	-0.97	0.52
Tries	Better	-0.23	0.68	0.46	3.37	-0.31	0.51	0.16	1.26	-0.05	0.76	0.14	0.93
	Balanced	-0.14	0.78	0.72	2.61	-0.29	0.54	0.32	1.45	0.02	0.82	0.23	0.98
	Worse	-0.10	0.81	0.94	2.58	-0.27	0.58	0.51	1.58	0.11	0.89	0.39	1.10
Kick Breaks	Better	-0.04	0.25	0.26	1.92	-0.04	0.22	-0.11	0.35	0.12	1.54	-0.10	0.30
	Balanced	-0.05	0.21	0.70	3.35	-0.05	0.21	-0.11	0.36	0.12	1.64	-0.09	0.35
	Worse	-0.05	0.22	0.75	4.35	-0.04	0.21	-0.08	0.41	0.21	1.80	-0.08	0.34
Conversion	Better	-0.11	0.23	0.06	1.29	-0.13	0.16	-0.12	0.44	0.28	1.72	-0.14	0.40
	Balanced	-0.11	0.21	0.14	1.55	-0.12	0.17	-0.14	0.38	0.39	1.88	-0.15	0.37
	Worse	-0.11	0.23	0.03	1.25	-0.12	0.16	-0.17	0.22	0.59	2.15	-0.17	0.33
Penalties	Better	-0.14	0.03	-0.04	0.70	-0.14	0.03	1.57	3.46	-0.07	0.44	-0.13	0.10
	Balanced	-0.15	0.03	0.01	0.99	-0.15	0.04	1.61	3.27	-0.08	0.40	-0.13	0.10
	Worse	-0.15	0.03	-0.13	0.48	-0.15	0.04	1.68	2.88	-0.08	0.42	-0.13	0.03
Try Causes	Better	0.03	0.87	0.05	1.31	-0.20	0.72	1.20	2.19	0.04	0.87	0.31	1.02
	Balanced	-0.07	0.81	0.00	1.45	-0.27	0.67	0.87	1.93	-0.06	0.82	0.13	0.92
	Worse	-0.18	0.74	-0.06	1.31	-0.35	0.61	0.49	1.78	-0.16	0.72	-0.07	0.81

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Try Assists	Better	-0.15	0.56	-0.07	1.17	-0.26	0.34	0.34	1.64	0.15	1.17	-0.15	0.67
	Balanced	-0.11	0.64	-0.12	1.16	-0.24	0.36	0.59	2.09	0.28	1.28	-0.12	0.73
	Worse	-0.08	0.67	-0.03	1.21	-0.24	0.38	0.74	2.08	0.44	1.42	-0.08	0.80
Handling Errors	Better	-0.15	0.74	0.72	2.71	-0.23	0.64	0.50	1.62	0.14	0.80	0.06	0.81
	Balanced	-0.13	0.76	0.81	3.35	-0.26	0.65	0.51	1.56	0.08	0.79	0.02	0.77
	Worse	-0.12	0.79	1.24	3.02	-0.29	0.60	0.44	1.49	0.09	0.78	0.00	0.79
Defensive Decisions	Better	-0.02	0.51	2.73	5.51	-0.03	0.58	0.01	0.68	-0.11	0.58	0.01	0.65
	Balanced	0.00	0.56	2.03	4.85	-0.04	0.58	-0.01	0.65	-0.14	0.55	-0.03	0.59
	Worse	-0.03	0.50	0.44	2.36	-0.07	0.55	0.01	0.62	-0.17	0.56	-0.04	0.57
Supports	Better	0.18	0.75	-0.12	1.91	-0.01	1.08	-0.08	0.95	-0.27	1.20	-0.01	0.54
	Balanced	0.15	0.74	-0.19	2.05	0.03	1.07	-0.02	1.09	-0.20	1.25	0.05	0.55
	Worse	0.14	0.75	-0.10	1.98	-0.02	1.07	0.12	1.08	-0.15	1.30	0.04	0.54
Try Saves	Better	-0.11	0.74	2.16	3.93	-0.13	0.75	-0.17	0.82	0.15	0.87	-0.12	0.75
	Balanced	-0.10	0.76	1.62	2.99	-0.07	0.81	-0.17	0.75	0.15	0.90	-0.12	0.72
	Worse	-0.09	0.76	1.60	2.99	-0.11	0.79	-0.15	0.78	0.16	0.89	-0.14	0.71
Both Try	Better	-0.03	0.31	1.23	4.47	-0.01	0.36	-0.06	0.35	-0.07	0.61	-0.14	0.29
	Balanced	-0.04	0.32	1.84	6.10	0.00	0.38	-0.01	0.40	-0.04	0.60	-0.12	0.28
	Worse	-0.02	0.32	1.66	4.36	0.00	0.37	-0.01	0.42	-0.01	0.58	-0.11	0.27

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Table 21. Descriptive statistics for position and match location.

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forward Attacking Play	Better	0.41	0.93	0.28	1.53	0.47	1.17	0.26	1.11	-0.60	0.71	-0.34	0.51
	Balanced	0.34	0.89	0.23	1.55	0.39	1.16	0.21	1.04	-0.66	0.68	-0.32	0.51
	Worse	0.39	0.86	0.78	2.36	0.62	1.41	0.47	1.13	-0.60	0.71	-0.21	0.48
General Play Kicking	Better	-0.26	0.29	0.18	1.58	-0.18	0.39	-0.23	0.50	0.87	1.65	-0.36	0.29
	Balanced	-0.27	0.27	0.22	1.77	-0.21	0.38	-0.24	0.55	0.86	1.62	-0.37	0.28
	Worse	-0.30	0.19	0.20	1.26	-0.14	0.34	-0.28	0.38	0.97	1.90	-0.31	0.24
Kick Pressure	Better	0.47	0.58	0.18	1.40	0.42	0.85	0.38	0.98	-0.20	1.06	-0.97	0.52
	Balanced	0.50	0.58	0.30	1.50	0.44	0.87	0.35	1.01	-0.19	1.04	-1.00	0.55
	Worse	0.49	0.54	1.03	1.40	0.51	0.83	0.14	1.26	-0.12	1.12	-1.04	0.66
Tries	Better	-0.13	0.80	0.61	2.45	-0.27	0.57	0.37	1.45	0.05	0.85	0.26	1.02
	Balanced	-0.18	0.73	0.82	3.21	-0.31	0.52	0.27	1.41	0.00	0.80	0.23	0.98
	Worse	-0.14	0.75	-0.50	0.38	-0.23	0.56	0.39	1.82	0.14	0.86	0.27	0.95
Kick Breaks	Better	-0.05	0.23	0.47	2.56	-0.05	0.22	-0.10	0.39	0.17	1.69	-0.09	0.35
	Balanced	-0.05	0.22	0.75	4.01	-0.04	0.20	-0.10	0.35	0.12	1.64	-0.09	0.31
	Worse	-0.03	0.14	-0.43	1.00	-0.03	0.18	-0.14	0.24	-0.05	1.17	-0.08	0.39
Conversion	Better	-0.11	0.22	0.06	1.23	-0.13	0.16	-0.13	0.40	0.47	2.03	-0.15	0.38
	Balanced	-0.11	0.22	0.13	1.59	-0.12	0.17	-0.15	0.34	0.35	1.78	-0.15	0.36
	Worse	-0.08	0.28	-0.28	0.25	-0.13	0.10	-0.20	0.13	0.50	2.39	-0.19	0.23
Penalties	Better	-0.15	0.03	-0.07	0.68	-0.15	0.03	1.58	3.33	-0.08	0.40	-0.13	0.10
	Balanced	-0.15	0.03	-0.01	0.94	-0.15	0.04	1.66	3.15	-0.07	0.43	-0.13	0.08
	Worse	-0.15	0.03	-0.10	0.11	-0.15	0.04	1.49	2.72	-0.09	0.34	-0.13	0.03
Try Causes	Better	-0.11	0.78	0.03	1.52	-0.29	0.66	0.79	1.95	-0.10	0.78	0.08	0.91
	Balanced	-0.04	0.83	-0.03	1.22	-0.26	0.68	0.93	1.98	-0.02	0.84	0.17	0.95
	Worse	0.02	0.85	-0.10	0.85	-0.26	0.65	1.68	3.11	0.04	0.90	0.08	0.87

Factor	Match Type	Forwards		Utility Back		Interchange		Interchange Forwards		Adjustables		Backs	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Try Assists	Better	-0.11	0.63	-0.12	1.02	-0.23	0.37	0.61	2.07	0.33	1.32	-0.10	0.74
	Balanced	-0.12	0.62	-0.06	1.30	-0.26	0.35	0.50	1.86	0.25	1.27	-0.12	0.73
	Worse	-0.01	0.77	0.47	2.31	-0.24	0.34	0.86	2.62	0.33	1.35	-0.29	0.43
Handling Errors	Better	-0.14	0.76	0.85	3.13	-0.26	0.63	0.46	1.53	0.10	0.79	0.01	0.78
	Balanced	-0.13	0.76	0.92	3.09	-0.25	0.64	0.54	1.60	0.10	0.79	-0.01	0.63
	Worse	-0.23	0.63	2.62	3.48	-0.37	0.49	0.22	1.39	0.01	0.73	0.11	0.81
Defensive Decisions	Better	-0.01	0.54	1.98	4.90	-0.06	0.56	0.01	0.62	-0.15	0.56	-0.03	0.58
	Balanced	-0.01	0.53	1.71	4.38	-0.04	0.58	0.00	0.68	-0.14	0.57	0.04	0.78
	Worse	0.05	0.56	-0.88	1.51	-0.09	0.57	-0.12	0.63	-0.20	0.45	-0.17	0.48
Supports	Better	0.19	0.74	-0.17	1.88	0.03	1.10	0.02	1.06	-0.19	1.28	0.05	0.54
	Balanced	0.13	0.74	-0.15	2.11	-0.01	1.04	-0.02	1.03	-0.22	1.23	0.02	0.55
	Worse	0.08	0.79	0.77	2.30	0.01	1.26	-0.32	1.33	-0.11	1.24	0.05	0.62
Try Saves	Better	-0.10	0.75	1.93	3.35	-0.11	0.77	-0.20	0.73	0.14	0.88	-0.14	0.71
	Balanced	-0.10	0.76	1.54	3.01	-0.07	0.81	-0.14	0.82	0.16	0.90	-0.10	0.74
	Worse	-0.22	0.65	4.70	9.14	-0.17	0.77	-0.23	1.00	0.13	1.03	-0.03	0.90
Both Try	Better	-0.02	0.31	1.64	4.42	0.01	0.37	-0.01	0.38	-0.04	0.62	-0.12	0.27
	Balanced	-0.04	0.32	1.63	6.12	-0.01	0.38	-0.04	0.40	-0.04	0.56	-0.13	0.29
	Worse	-0.02	0.25	0.89	4.39	-0.02	0.34	-0.13	0.44	-0.03	0.87	-0.12	0.26

Figure 7 (Node 2) depicts the tree for utility backs and was first split by *quality of opposition*, where the likelihood of winning against 'Better' opposition was 46% (Node 8), compared to 68.3% and 80.4% when competing against 'Balanced' and 'Worse' opposition, respectively. Continuing to the left of the tree, Node 8 was then split by 'Defensive Decisions', whereby the likelihood of winning dropped to 29.6% when Utility Backs produced ≤ 0.63 'Defensive Decisions' (Node 30), but improved to 65.2% when producing >0.63 'Defensive Decisions' (Node 31).

Figure 8 depicts the tree for interchange forwards (Node 3) and was first split by *quality of opposition*. When facing 'Better' opposition, the likelihood of winning dropped to 21.4% (Node 11) whereas it increased to 72.5% (Node 13) when facing 'Worse' opposition. Continuing further down the left-hand side of this tree, Node 11 was split by 'Try Causes'. When Interchange Forwards committed fewer try causes (≤ -0.56, Node 39) against 'Better' opposition, their likelihood of winning improved from 21.4% to 36.6%. However, the greater the number of 'Try Causes' that these players made, the less likely they were to win games; Node 40 ('Try Causes' >-0.55, <0.59) success rate dropped to 25.4%, while for Node 41 ('Try Causes' >0.59), the likelihood of winning dropped to 11.5%.

Finally, Figure 9 depicts the tree for adjustables (Node 4) that was first split by *quality of opposition*, with a winning probability of 26.3% when competing against 'Better' opposition, which dropped to 76.1% when competing against 'Worse' opposition. Continuing to the right of Node 4, to Node 16 (*quality of opposition* = worse), data was further split by *match type*. For example, when adjustables competed against a 'Worse' opposition during 'Runaway' matches, the probability of winning was 93.9% compared to 66.9% during 'Close' matches. This combination of PIs led to the highest probability of winning for the adjustables' positional group.

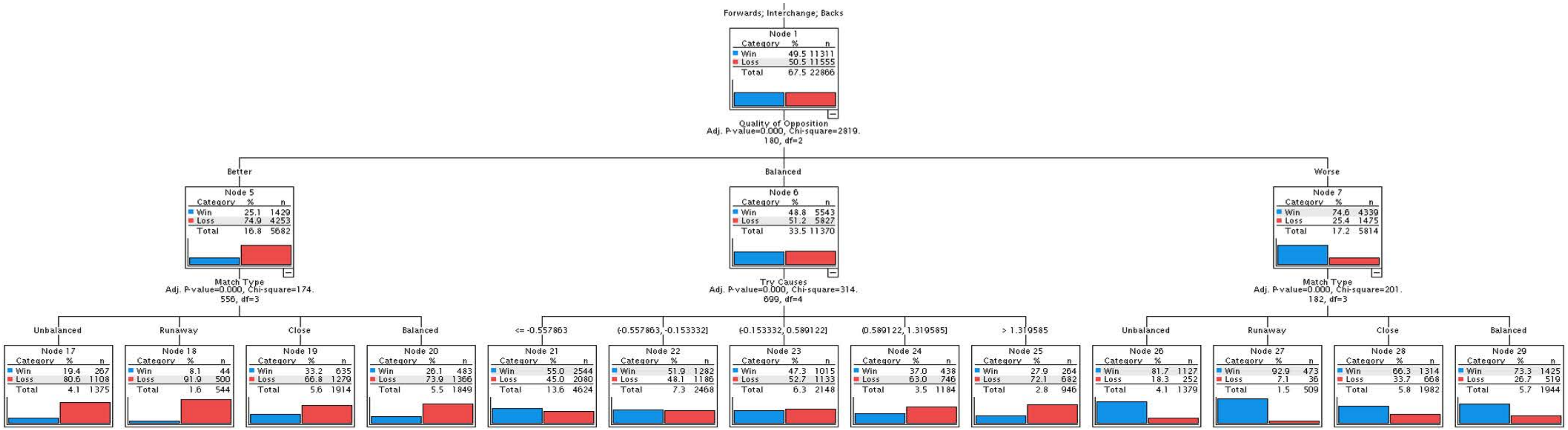

Figure 6. Exhaustive CHAID model of match outcome as influenced by Forwards, Backs and Interchange players and various response variables and Performance Indicators

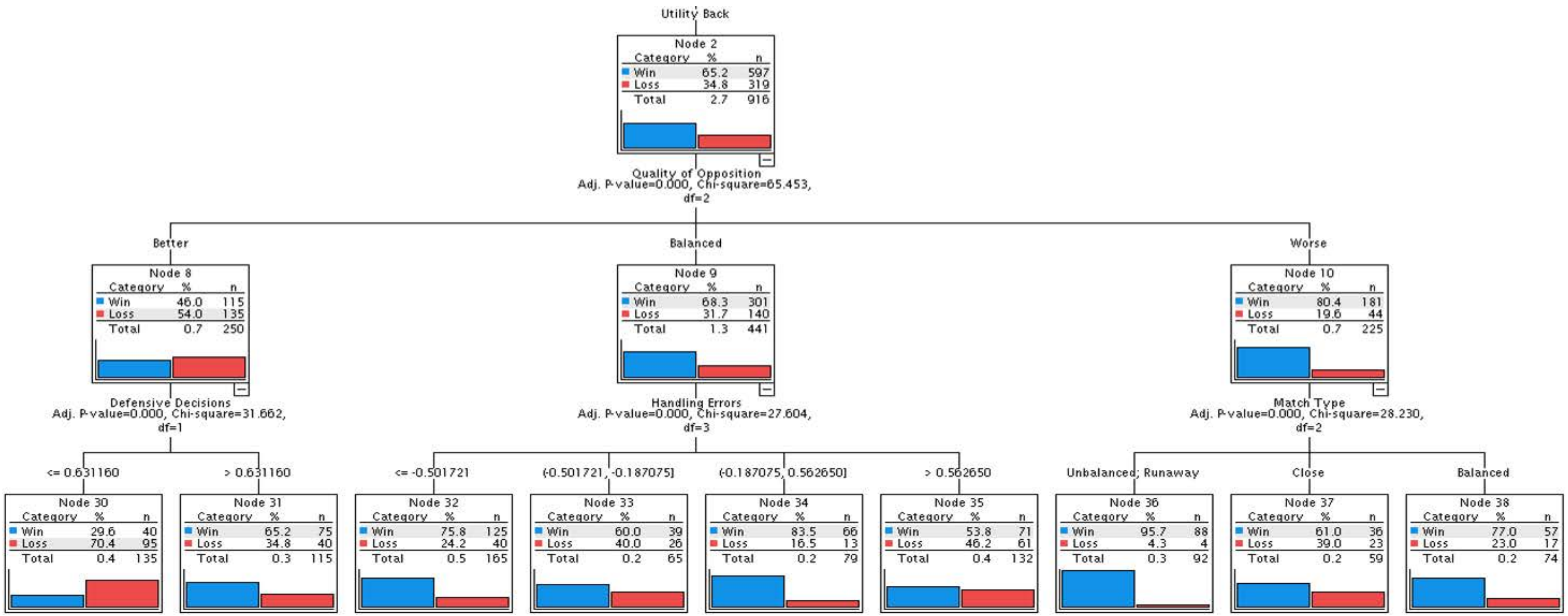

Figure 7. Exhaustive CHAID model of match outcome as influenced by Utility Backs and various response variables and Performance Indicators

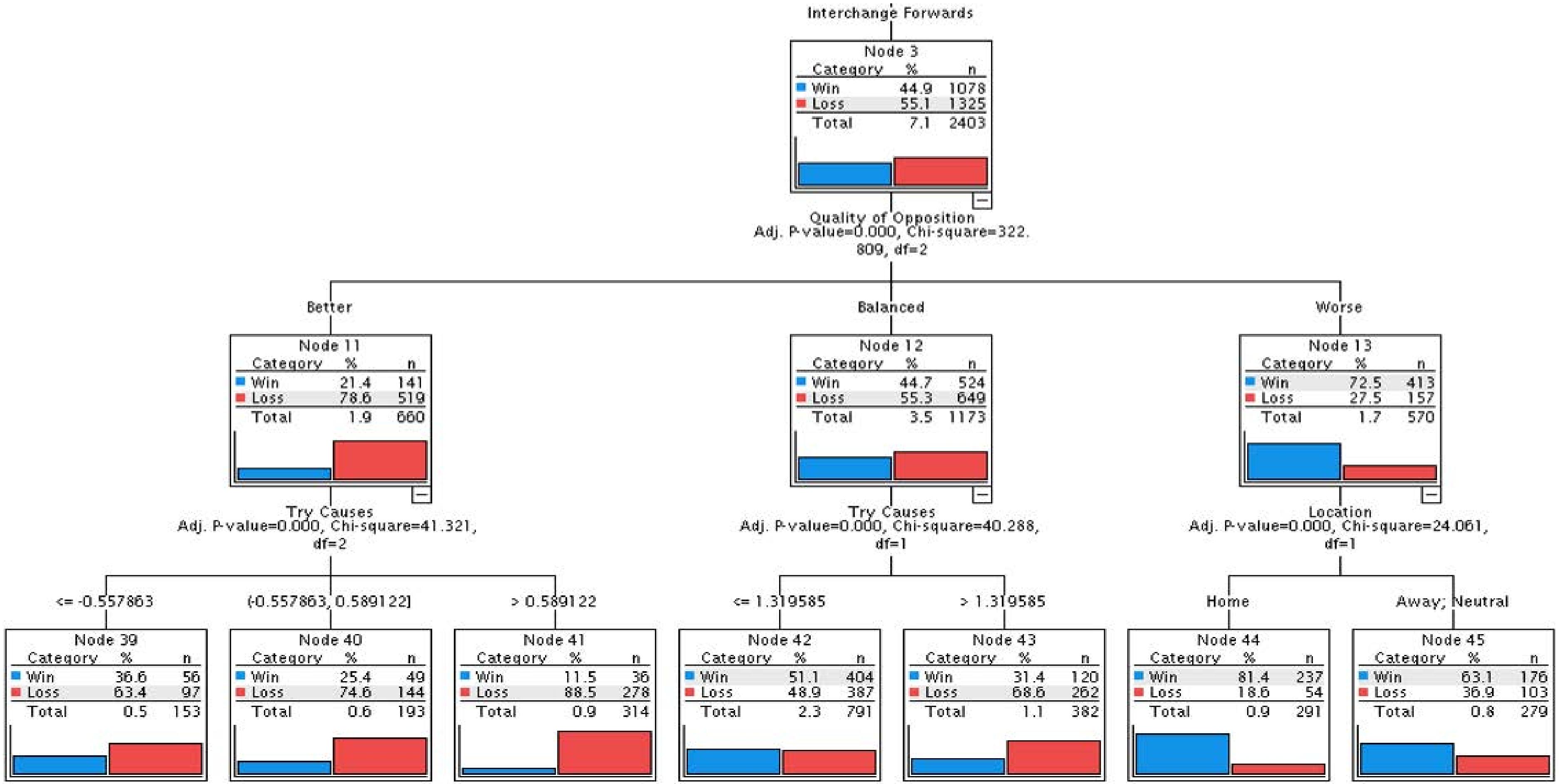

Figure 8. Exhaustive CHAID model of match outcome as influenced by Interchange Forwards and various response variables and PIs.

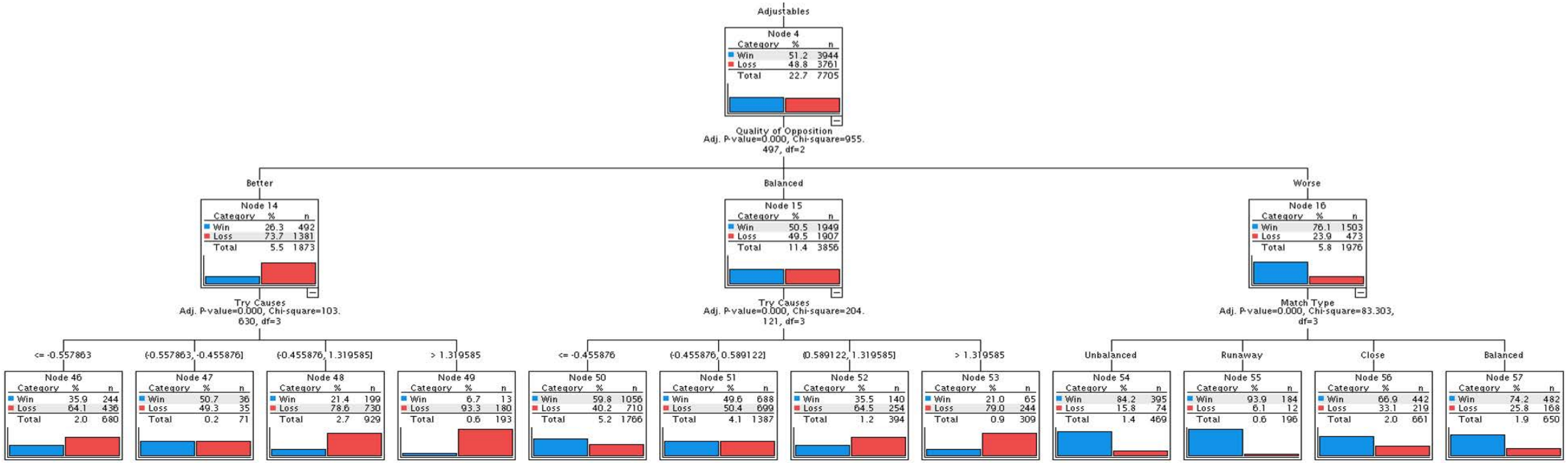

Figure 9. Exhaustive CHAID model of match outcome as influenced by Adjustables and various response variables and PIs.

6.5 Discussion

This chapter investigated the effects of different match-related contextual variables on positional groups and the likelihood of success (match outcome) in the NRL. Results showed that forwards, interchange players and backs were grouped together, exerting similar influences on match outcome irrespective of match context. Conversely, interchange forwards, utility backs and adjustables might have a more definitive role in match outcome, as seen in the resulting trees. Similar findings have been noted in Chapter 5 and elsewhere (Bennett et al., 2016; Sirotic et al., 2011), but work had yet to compare the relative contribution to overall team performance, as done here. The findings that specific positional groups have relatively (dis-)similar contributions to team performance could have several implications for coaching staff, particularly with respect to team selections. For example, by improving the 'catch-pass' of utility backs – thereby assisting with a potential reduction in the frequency at which 'Handling Errors' may occur – a team could improve their likelihood of success beyond 54% (Figure 7; node 35) to as much as 84% (Figure 7; node 34). Similarly, a defence-orientated coach may interpret the same finding such as that by increasing defensive pressure on utility backs – thereby potentially increasing 'Handling Errors' – an opposing team may increase their opportunity to be successful. Whilst acknowledging 'Handling errors' rely on a number of additional variables, the aforementioned examples provide an illustration of the practical applications achievable from the current findings. Interestingly, the three individually split positions include key position (adjustables) and interchange players (interchange forwards and utility backs), which would mean the decision-making regarding team selection, particularly around these positions, is even more important for team performance. Further, it would suggest that positional-specific training also may be important for improving the overall team success – namely, utility backs improving defensive decisions or interchange forwards working on their defensive movements and decision making to prevent try causes. Our point here is that by understanding that these positional groups can have an impactful influence on team success, coaches can carefully design task-specific training activities, select certain players to fulfil roles and plan innovative playing strategies.

It was interesting to note the omission of attacking variables from the final model, with defensively related variables seeming to have a greater influence on match outcome. Research had suggested that attacking PIs such as try assists, run metres, offloads and line breaks provided the greatest explanation for match outcome (and ladder position) in the NRL from a team level (Woods et al., 2017d), which has been supported by findings in Chapter 3 and other recent team level studies of RL (Parmar et al., 2018a; Parmar et al., 2018b). Whilst research has identified that manufacturing scoring opportunities enhances the likelihood of success (Woods et al., 2017d), the current results highlighted that reduced errors in both attack and defence are more important from a positional level. Our findings indicate that it would be beneficial for teams to focus on position-specific, defensive activities during training to aid overall team success. For example, if improving the defensive decisions (Factor 11; intercepts and missed tackles) of Utility Backs (Figure 7) can improve the likelihood of winning from 29.6% (node 30) to 65.2% (node 31), then performance preparation frameworks could prioritise the decision making and tackle selection of such players. This would also support the results of previous research, which highlighted that in conjunction with maintaining possession and generating scoring opportunities, defensive efficiency was important for team success in the NRL (Chapter 3).

The results of the exhaustive CHAID highlighted that the response variables chosen for this chapter had a greater influence over the positional influence on match outcome than any of the technical skill metrics previously reported in Chapter 5. This indicates that additional analyses could be used to enhance our current understanding of the relationship(s) that might exist between the technical performance of various positional groups and how this may influence match outcome, as at present, just three of the fourteen PIs were retained in the model. Although, the model does provide novel insight into how different positional groups, PIs and response variables interact to influence team performance. Further to this, the interpretations of these insights may then be dictated by the style of play for a specific team, or whether it is being viewed from the perspective of an offensive or defensive oriented coach (as per previous examples above). Nevertheless, the model outputs can offer interpretable insight for coaches in understanding how different PIs (and contextual factors) contribute to positional and team performance, enabling tactical insight for coaching and performance staff, specifically regarding team selections, training and game-planning.

This chapter is not without limitations that require brief recognition. Firstly, it is worth considering that different clubs each have a unique way of playing and thereby will inherently utilise their personnel differently. The results of the chapter offer an abstract and generalisable insights, however the nuanced interactions (e.g., manipulating PTB speed in defence to reduce the likelihood of opposition teams scoring) that may occur at a team level may be more practical, which may require further investigation. Secondly, given recent rule changes introduced in the 2020/21 seasons (e.g., 'six again' and reduced scrums), and the varying implications of COVID-19, it is possible that the way in which different positional groups are utilised has changed relative to the sample used within this chapter. It would be interesting for follow up work to, therefore, explore differences in competition trends before and following COVID-19 restrictions. Thirdly, the data utilised in this chapter was discrete, and thus insights should be made relative to its nature. The addition of spatiotemporal data, for example, may add further depth to what was offered here through the consideration of context surrounding the noted action.

6.6 Conclusions & Practical Implications

This chapter modelled the relationship between match-related contextual factors on positional performance and match outcome in the NRL. A moderate level of classification accuracy was observed, justifying the use of this approach for further examination into the interaction between positional performance, match factors and success. Defensive actions and poor attacking skill significantly influenced match outcome greater than PIs that helped generate scoring opportunities in attack. Further, interchange forwards, utility backs and adjustables independently impacted upon the likelihood of team success when compared to forwards, interchange players and backs. These results offer coaches and analysts in the NRL with interpretable and practically useful insight to complex interactions.

6.7 Key Points

- Unique contributions of positional groups to overall team success in elite rugby league were identified, with interchange forwards, utility backs and adjustables each exhibiting a more definitive team role than others.
- Contrasting to team level research, defensive actions and poor attacking skill influenced match outcome greater than other PIs.
- Consideration of the complex interactions between match-related contextual variables, PIs and positional groups may provide practical insight for coaches regarding training design, player selection and game tactics.

Chapter 7: Thesis Summary, Conclusions & Future Research Directions

7.1 Summary

The primary aim of this doctoral thesis was to explore how the use of various analytical techniques could resolve team and positional performance characteristics explanatory of success in the NRL. These analytical techniques first discussed and introduced in Chapter 2 laid the foundation for the ensuing studies in Chapters 3 – 6 to address the four secondary aims of this thesis. Generally, the novel analytical techniques employed in each of the chapters were successful in achieving the chapter's aim, broadly identifying various team and positional performance characteristics important for success in the NRL. Accordingly, the following sections will summarise the main findings from each of these studies.

7.1.1 Key Technical and Tactical Team Characteristics in Rugby League

Chapter 3 investigated team playing styles in the NRL over five seasons using PCA. It was identified that nine 'Factors' were explanatory of seasonal team performance variance, with these 'Factors' then being used to describe the emergent styles of play that were important for distinguishing differences between ranking higher (or lower) on the ladder. It was identified that the relative importance of these nine 'Factors' differed across seasons, with four showing an effect against season ranking. Additionally, two 'Factors' showed a large effect against season, and a moderate effect against the combined effects of season and rank. As discussed in Chapter 3, it was suggested that there has been a recent shift in the emphasis of play, with a specific focus on deliberately designing match-tactics that best exploit noted playing styles.

Building on these findings, Chapter 4 explored the effect of contextual match-factors on team playing styles and subsequent team success. Discriminant function analysis was unsuccessful in meaningfully resolving playing styles for match type, team quality, and match location. Although, it was able to correctly classify 81% of matches based on match outcome, using four of the identified playing styles: ‘attacking play’, ‘linebreaks’, ‘handling errors’ and ‘conceded linebreaks’. These results corroborated those of Chapter 3, which highlighted the importance of attacking ball control, coupled with relative defensive efficiency in explaining match outcome, regardless of team quality, match location or match type. However, it was also suggested in Chapter 4 that further extrapolating the information gathered in both Chapters 3 and 4 over the time-course of a match could give real-time feedback on the likelihood of winning, and insight into areas of the game that could be augmentative of this.

Collectively, both Chapter’s 3 and 4 successfully identified team playing styles important for success in the NRL over recent seasons across varying match-contexts. However, in contrast to other team-level research conducted elsewhere (Gómez et al., 2011; Lago-Peñas et al., 2016; Sapp et al., 2018), the results of Chapter 4 suggest that NRL teams do not adopt a specific playing style with regards to match location (i.e., Home and Away). While this is not suggesting that there is not a home advantage that teams exploit in the NRL, preliminary investigation into playing styles and match location indicate that it is less of a factor in determining how teams choose to play. Comparable results were highlighted with regards to both team quality and match type, with the chosen analyses unable to meaningfully resolve specific styles of play important for either of these match-contexts. On the contrary, when considering the results of Chapter 3 – specifically the increased importance of attacking PTB speed and supports – the recent rule change introducing the six-again rule in the 2021 NRL season may see an even greater importance on teams’ game-planning opportunities around generating a greater number of ‘quick’ PTBs. This, therefore, offers an enticing avenue for future research.

7.1.2 Key Positional Characteristics in Rugby League

Chapter 5 investigated playing positions and their importance to team success in the NRL. Through the use of PCA, 14 ‘Factors’ were identified and included in a two-step cluster analysis. From this, six positional groups were identified: ‘forwards’, ‘backs’, ‘adjustables’, ‘interchange’, ‘utility backs’ and ‘interchange forwards’. These resulting clusters were achieved with a good level of classification accuracy, with 89.4% of all players assigned to their *a priori* playing position. One of the more notable findings from this chapter related to the identification of two additional positional groups, neither of which had been reported in the literature prior to this work. These new groups were formed as ‘combinations’ of other playing positions; ‘utility backs’ were a combination of adjustable and backs, and ‘interchange forwards’ were a combination of forwards and interchange players.

Chapter 6 extended these findings by exploring the influence of match-related contextual factors on positional contribution to match outcome. Using both the previously identified positional groups and ‘Factors’ from Chapter 5, the exhaustive CHAID algorithm was used to model the effect of match type, match location and quality of opposition on the positional contribution to match outcome. The resulting model revealed four primary splits with a model accuracy of 66%, which included interchange forwards, utility backs, adjustables, and a group containing the remaining three positional groups. These splits suggested that interchange forwards, utility backs and adjustables had a definitive role within the explanation of match outcome relative to the remaining positional groups. Further, there appeared to be a greater emphasis on the importance of defensive actions at a positional level than at a team level, as shown in Chapter's 3 and 4. With that said, however, the results of Chapter 3 did indicate that improved defensive efficiency was an important factor for team success, and thus performance preparation frameworks could prioritise the decision making and tackle selection of players, thereby further enhancing both individual and team performance.

7.2 Thesis Strengths and Limitations

In the second chapter, I expressed the need for further guidance and information regarding the application of various analytical techniques for the handling of the "ever-growing sea" of data for current and aspiring sports performance analysts within the sport of RL. From here, I then suggested that there was a lack of information regarding the utility of several increasingly common analytical techniques within the RL literature – thus it was the aim of this thesis to extend work seen in other sports to the specific context of RL. As such, a clear strength of this thesis has been in its ability to highlight the efficacy of several analytical techniques – PCA, discriminant analysis, decision trees and clustering – for the identification of team playing styles, key positional characteristics, and the effect of various match-contexts on both. Each of these published chapters were able to meaningfully extend the current state of the literature by highlighting the various characteristics important for team and individual performance using unsupervised clustering and classification techniques – something that had yet to be explored within the NRL. Doing so has helped bridge the gap between applied research and practice through highlighting how the use of analytical techniques common to disciplines outside of sport science could be used in practice to assist with day-to-day operations for NRL teams.

It would also be remiss to not acknowledge the changes that have occurred over recent seasons – such as rule changes introduced in the 2020-22 seasons (e.g., ‘six again’ and reduced scrums), and the varying implications of the COVID-19 pandemic (e.g., changes to travel arrangements and crowds). These key factors could have led to a change in the tactical organisation of players and teams, which may implicate the immediate practicality of my doctoral work, thereby exposing its key limitation. Nevertheless, it was the aim of this thesis to explore the use of novel analytical techniques for the resolution of various team and positional performance characteristics important for success in the NRL, guiding how future analytes in the NRL may go about tackling questions like those addressed in this thesis. Accordingly, a selection of data reduction, clustering and decision support analyses were used, and ultimately were shown to enable greater understanding of the tactical and technical characteristics important for match success in RL from both a team and positional level. Thus, I hope that this thesis will contribute to the growth of performance analysts within RL and assist with further advances in our understanding of what is important for success in the NRL.

7.3 Future Research Directions

As sports technology companies continue to explore ways of capturing and integrating various forms of data, it has become increasingly important for sports performance analysts to understand how various analytical techniques could be used to assist with the resolution of actionable insights gleaned from the rising volume of data generated. For example, sports technology companies have been working on products that are able to integrate spatio-temporal (via Global Positioning Systems) and technical data points from matches into a singular data series (and linked to video match-events). Doing so may enable a deeper analysis and provide further context into areas of match-performance that are not fully understood and provide greater insight into what exactly takes place prior to specific match events such as scoring or turnovers (i.e., increased ball-in-play creating cumulative fatigue prior to specific match events occurring). With Chapter 3 and 4 highlighting the importance of attacking ball control and defensive efficiency in explaining match outcome, we have begun to better understand some of the technical and tactical areas of match-performance. Layering additional spatio-temporal data onto this information may provide deeper insights for coaching and performance staff on the peak physical demands required for their athletes to best perform during these periods of the game. In order for this to occur, however, sport performance analysts need to be able to select analytical approaches capable of not only handling large amounts of data, but different types of data concurrently – different to some of the techniques discussed in this thesis (Goes et al., 2020; Sawczuk et al., 2021). Research exploring the aggregation of technical and spatio-temporal data is something that has recently been discussed in sports such as soccer (Memmert et al., 2017; Olthof et al., 2015; Rein & Memmert, 2016) and AF (Teune et al., 2022; Vella et al., 2021; Wing et al., 2022), guiding the examination of tactical team formation. Thus, future research in RL could look to explore how the use of such spatiotemporal data could inform team tactics in the NRL. This information could also assist in a collaborative approach to the design and implement specific training activities by coaching and high-performance staff, with the aim to that place their athletes under similar levels of fatigue to improve tolerance and execution during similar phases during competition. This leads to another interesting avenue for this doctoral thesis – that being, exploring how contemporary theories of skill acquisition could be woven into the analysis of match and training activities to help with the design of representative tasks that support player learning. Examples of such research in team sport have been shown in the recent work of Browne et al. (2020), with this offering a guiding platform for research in RL to follow along with.

7.4 Conclusions

It was the primary aim of this doctoral thesis to explore the use of various analytical techniques for resolving team and positional performance characteristics explanatory of success in the NRL. The techniques first discussed in Chapter 2 were then used to further examine the technical and tactical characteristics important for positional and team success in the NRL. Generally, the novel analytical techniques employed through Chapters 3-6 were successful in achieving the chapter's aim. The information gleaned from this thesis can thus be used by aspiring performance analysts, particularly within the sport of RL, as a starting point for team and positional analyses. It is expected that the results of this thesis would assist further research in bridging the gap between both research and practice, as well as help guide future performance analysis research within the sport of RL.

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Appendix A

Human Ethics Approval for Chapters 3-7. Ethics approval for Chapters 3 and 4 are covered under application approval H7968.

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