MODELLING PLAYER PERFORMANCE DATA FOR ORGANISATIONAL DECISION SUPPORT IN PROFESSIONAL AUSTRALIAN RULES FOOTBALL

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DOCTORATE OF PHILOSOPHY

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ABSTRACT

Within contemporary professional team sport organisations, operational decisions are increasingly becoming informed by objective data. Within the elite competition of Australian Rules football, the Australian Football League (AFL), an abundance of player and team performance data is collected and reported. However, the extent to which this data has been used in the team sport notational literature to inform organisational decision-making is limited. This thesis utilises a particular algorithmic player rating system, the 'AFL Player Ratings', and the subcategories used to construct this metric. Each study of this thesis models various applications of player performance data and presents it in a format for the purpose of providing organisational decision support to AFL clubs. The first study of this thesis establishes the validity of the AFL Player Ratings system. The second study identifies how performance profiles created from the proportion of rating points in each AFL Player Rating subcategory can be used to classify players into *a priori* determined player role categories. Additionally, it determines a level of similarity between the playing styles of each individual player competing within the AFL. The third study developed two separate models to objectively benchmark player performance, and to identify stages of peak performance and specific breakpoints longitudinally. The final study of the thesis investigated the relationship between subjective ratings of performance and basic player performance indicators, in order to gain an understanding of the extent to which human decisions are related to measurable aspects of a player's performance. It also looked to compare subjective and objective ratings of player performance. Each of these studies address a different use of the data operationally, and provide a framework for clubs competing in the AFL. It outlines how objective player performance data can be modelled to inform various aspects of team and player individuality, value and potential, with a specific focus on supporting team selection, player drafting and recruitment.

STUDENT'S DECLARATION

Doctor of Philosophy by Publication Declaration

"I, Samuel McIntosh declare that the PhD thesis by Publication entitled

Modelling player performance data for organisational decision support in professional Australian Rules football

is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

Signed: [redacted] Date: 24/10/2019

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PART A:

DETAILS OF INCLUDED PAPERS: THESIS BY PUBLICATION

Please list details of each Paper included in the thesis submission. Copies of published Papers and submitted and/or final draft Paper manuscripts should also be included in the thesis submission

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PUBLICATIONS ARISING DURING CANDIDATURE

The following work has been published in peer-reviewed journals in support of this thesis:

1. **McIntosh, S**., Kovalchik, S., & Robertson, S. (2018). Validation of the Australian Football League Player Ratings. *International Journal of Sports Science & Coaching*, *13*(6), pp. 1064–1071, doi:10.1177/1747954118758000. (Chapter Three).
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4. **McIntosh, S**., Kovalchik, S., & Robertson, S. (2019). Comparing subjective and objective evaluations of player performance in Australian Rules football. *PLOS ONE*, 14(8), e0220901. doi:10.1371/journal.pone.0220901. (Chapter Six).

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The following work has been presented at scientific meetings in support of this thesis:

1. **McIntosh, S**., Kovalchik, S., & Robertson, S. (2018). Multifactorial benchmarking of longitudinal player performance in the Australian Football League. Presented at *World Congress of Performance Analysis of Sport XII.* (Preliminary work relating to Chapter Five).
2. **McIntosh, S**., Kovalchik, S., & Robertson, S. (2019). Comparing subjective and objective evaluations of player performance in Australian Rules football. Presented at *9th World Congress on Science and Football.* (Preliminary work relating to Chapter Six).

AWARDS ARISING DURING CANDIDATURE

Victoria University College Centenary Award (2016-2019) – Awarded to a graduate research student who has demonstrated academic excellence, and is conducting research that is strategically aligned with their college’s research focus.

Routledge Young Researcher Award (2018) – Awarded to best presentations by researchers under 35 at *World Congress of Performance Analysis of Sport XII*.

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LIST OF SYMBOLS AND ABBREVIATIONS

+	Plus
±	Plus or minus
%	Percent
<	Less than
>	Greater than
≤	Less than or equal to
β	Beta coefficient
n	Number of participants
p	P-value
r	Correlation coefficient
ANOVA	Analysis of variance
AFL	Australian Football League
AFLW	Australian Football League women's competition
AF	Australian Rules football
CART	Classification and regression tree
CHAID	Chi-squared automatic interaction detection
CI	Confidence interval
GEE	Generalised estimating equations
Gen Def	General Defender
Gen Fwd	General Forward
GPS	Global positioning system
GWS	Greater Western Sydney
IFPR	Inside Football Player Ratings

Key Def	Key Defender
Key Fwd	Key Forward
LPS	Local positioning system
Mid	Midfielder
Mid-Fwd	Midfield-Forward
NBA	National Basketball Association
PART	Partial decision tree
PECOTA	Player empirical and optimisation test algorithm
PI	Prediction interval
PSRE	Player specific random effects
SD	Standard deviation
SE	Standard error

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CHAPTER ONE – INTRODUCTION

Chapter Overview

This chapter outlines the background and objective of the thesis (section 1.1), provides an introduction to Australian Rules football (AF) to add context for the analyses contained in the thesis (section 1.2), and outlines the structure of the thesis (section 1.3).

1.1 Background and objective of the thesis

The utilisation of objective performance data to support decisions in an elite sport setting has been shown to both play a role in improving performance outcomes, as well as reducing the financial costs associated with organisational processes, such as talent identification (Kuper, 2012; Ofoghi, Zeleznikow, MacMahon & Raab, 2013; Pion, Hohmann, Liu, Lenoir & Segers, 2016; Wright, Atkins, Jones & Todd, 2013). Organisations regularly face decisions regarding player identification and selection, which naturally involves some level of consideration about the positive and negative attributes in which each player would bring to the team/club (Tavana, Azizi, Azizi & Behzadian, 2013; Trninić, Papić, Trninić & Vukičević, 2008). At a macro level this relates to decisions regarding player recruitment, including which players to draft, as well as the length of contract and financial remuneration to offer, whilst maintaining total player payments (i.e., within a league salary cap). On a micro level, this relates to decisions regarding weekly team selections, including identifying optimal team line-ups and replacing injured players.

As in many other professional team sports, objective player performance data is collected and reported routinely in Australian Rules football (Robertson, Gupta & McIntosh, 2016). In the elite competition of AF, the Australian Football League (AFL), as well as some feeder competitions (i.e., national under 18 championships, and second-tier state leagues), clubs can access performance data from a commercial statistics provider (Champion Data Pty Ltd., Melbourne, Australia). Though some of this data is publically available for use by researchers and the general public, much of the more sophisticated statistics are only available with commercial licences. Despite this increased development of objective performance data in team sports, the advancement of its application between each sport has varied. This disparity has arisen for various reasons. Some specific examples include the level of complexity determining objectively quantifiable outcomes that emanate directly from player actions (Duch, Waitzman & Amaral, 2010), as well as, some sports simply receiving greater attention as a result of increased resources (Sarmento et al., 2014). In comparison to various other professional sports, in invasion sports such as AF quantifying what each player contributes to the overall team performance is inherently harder to determine (Gerrard, 2007). Additionally, in comparison to some other professional invasion team sport leagues, particularly the European (i.e., soccer) and North American (i.e., basketball, American football) team sports leagues, AF has less resources (Hutchins, 2016). As such, the volume of research outlined in AF within this space is considerably behind that in many other team sports.

The success of the Oakland Athletics in the Major League Baseball during the early 2000's was a catalyst for the implementation of detailed statistical analyses to better evaluate performance data in team sports (Stewart, Mitchell & Stavros, 2007). In the coming years there was an increase in research developed in this area, such as that by Hakes and Sauer (2006), who undertook an economic evaluation of the processes taken by the Oakland Athletics to exploit the inefficiency in batters' salaries, with respect to the contribution of specific skills to winning games. Other similar research was prompted to consider whether similar applications could be implemented in a wider variety of sports. So much so that in 2007 the *International Journal of Sport Finance* dedicated an entire issue to *Moneyball*, and its application within other sports. Specifically, there were various studies undertaken to assess applications with regards to complex invasion team sports such as basketball (Berri, Brook & Schmidt, 2007), ice hockey (Mason & Foster, 2007), as well as AF (Stewart et al., 2007).

Due to the complex nature of invasion team sports, as well as the common misunderstandings relating to a data driven focus towards decision-making, the prevalence of support applications within elite level sporting organisations remains mixed (Hutchins, 2016; Rein & Memmert, 2016). Common misunderstandings typically relate to the difficulty comprehending how, and to what extent objective based decisions can provide improved outcomes as compared to the current decision making processes of organisation (Massey & Thaler, 2013). As such, though the abovementioned literature exists, applying the findings of research within a professional setting faces further barriers. Alamar and Mehrotra (2011) best outline this in their article 'Beyond Moneyball: The rapidly evolving world of sports analytics' where they state:

"despite the remarkable growth in the amount and variety of data available for examination and analysis, the world of sports analytics still faces the same ubiquitous challenge: How to get meaningful information into the hands – and minds – of the people who are in a position to make effective use of it".

As this barrier still exists in many professional sporting organisations, one of the motivations of this thesis in part attempts to overcome this ongoing challenge. The overarching objective of this thesis is to model player performance data for organisational decision support applications in professional AF. This thesis contributes to the increasing amount of research focused on modelling player performance data to explain individual player performance in team sports; with the specific intent to bridge the gap between research and competition in AF. By adapting commonly used methodologies in other dynamic team sports, this thesis utilises available player performance data to create simplified and objective applications which can be used to support decisions which professional sporting organisations face. Each of the studies in this thesis look to outline how objective decision support can help to overcome the common misunderstandings relating to the ability to improve overall organisational decision making. Providing there is the opportunity and ability to get this meaningful information into the *hands* of key decision makers, the applications created in this thesis will enable this information to get into the *minds* of those people in a position to make effective use of it.

1.2 Australian Rules football

Australian Rules football is an invasion team sport which is played on an oval field between two opposing teams consisting of 22 players each (18 on the field and four interchange). Field size varies in length and width (between 135 and 185 metres in length, and 110 and 155 metres in width), and is outlined by specific areas. These areas include the centre square and circle, 50 metre arcs from each goal, as well as a goal square and four goal posts at each end of the field (two central posts are ‘goal posts’, whilst the outside post a ‘behind posts’). Figure 1.1 outlines an example of these field markings as shown in the official laws of the game (Australian Football League, 2017). The ball is moved about the ground by kicking, handballing, or running and carrying the ball. To kick the ball, it can be released from the player’s hands onto their foot, or alternatively by kicking the ball straight from the ground. A handball is achieved by holding the ball in one hand, and striking it with a closed fist created by the other hand. Scoring is achieved by kicking the ball between the goal posts at either end of the field. A goal (worth six points) is scored when the attacking team kicks the ball over the goal line, which is outlined between the two central goal posts. A behind (worth one point), is scored when the attacking team kicks the ball over one of the behind lines, which are outlined between one of the central goal posts and the adjacent behind post. Alternatively, if the ball strikes either of the goal posts, or travels over either the goal line or behind lines, but was last touched by the opposition, or by a body part other than the foot of the attacking team, it also counts as a behind.

Compared to most other invasion team sports, play is less structured, with players not constrained by an offside rule (i.e., soccer and rugby), or restricted to certain field zones (i.e., netball). Each match consists of four 20 minute quarters, where players can substitute at any stage (in the AFL, a rotation cap exists limiting each team to a maximum of 90 interchanges per game). The dynamic, low structured nature of AF allows for players to perform a variety of roles across the entire field of play, and requires the athletes to have a unique physical profile and set of technical and tactical qualities (Gray & Jenkins, 2010; Woods, Veale, Fransen, Robertson & Collier, 2018). Despite this dynamic and low structured nature, general positional roles do exist, and are important considerations for quantifying performance in AF. Further to this, this thesis has included an objective exploration of player roles in chapter four.

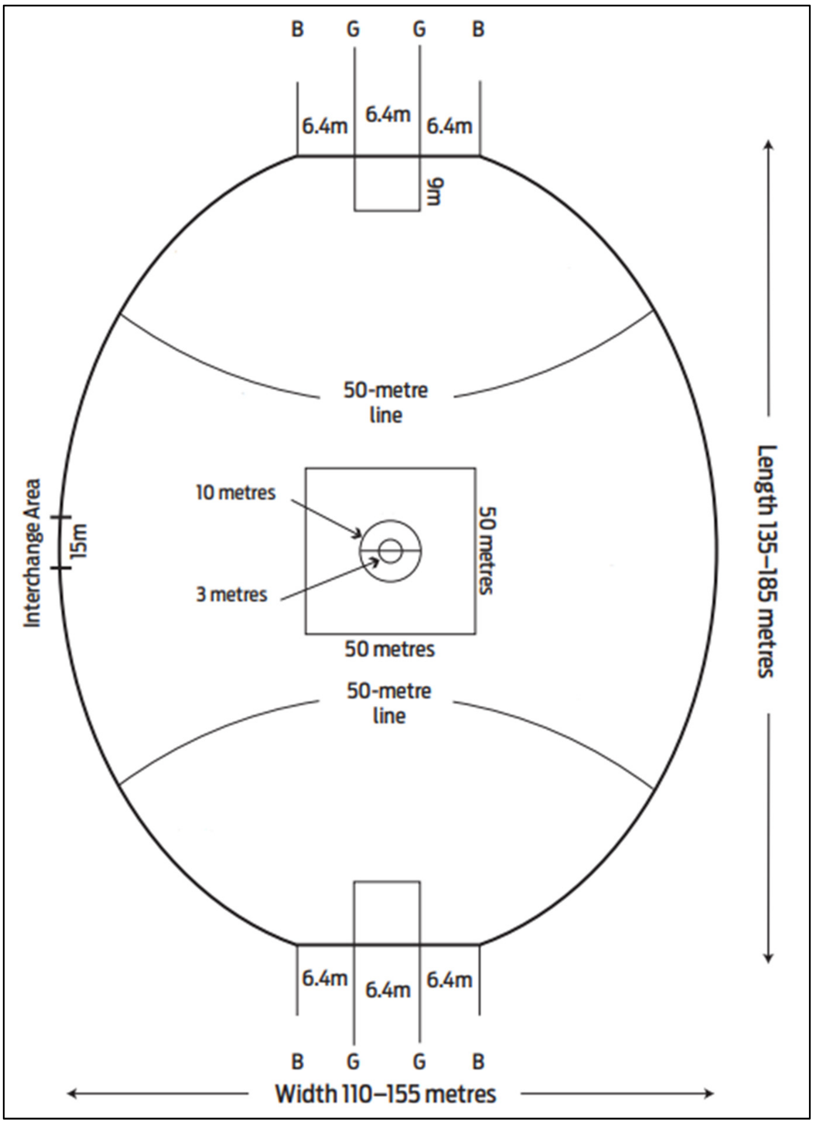

Figure 1.1 Outline of an Australian Rules football playing field. 'G' indicates goal posts; 'B' indicates behind posts.

The AFL is a multi-billion dollar sports industry which is continuing to grow (Gray & Jenkins, 2010). Participation levels in AF are increasing, attendance at AFL matches is at an all-time high, and in 2015 a record breaking deal was struck for the broadcasting rights (Australian Football League, 2018). To coincide with these growths is increasing player payments (Australian Football League, 2018). As a competition, the AFL is one of the most regulated professional sporting leagues in the world, whereby the clubs are subject to both a reverse order draft and a salary cap (Cook & Davies, 2012). The reverse order draft was introduced into the Victorian Football League (the predecessor to the AFL) in 1986, based on the system devised by the North American competition the National Football League (Davies, 2006). The draft structure is centred on the principle that the lesser performing teams from the previous season have the opportunity to select first from the current years prospective recruits, with the intention of improving competitive balance (Downward & Dawson, 2000). The salary cap was implemented in 1987, and was similarly introduced with the intention of improving competitive balance across the competition, by regulating what clubs can spend annually on player payments (Cook & Davies, 2012).

In addition to the abovementioned measures, in 2015 the AFL took a further step to improve competitive balance by implementing a ‘soft cap’, which limits what clubs can spend within their football department, outside of player payments. This includes (but is not limited to): staff wages (i.e., coaches, analysts, medical, fitness, recruiting, administration, finance personnel involved in contract negotiations, property stewards), funding for an affiliate secondary league team (i.e., a team competing in the Victorian Football League, North East Australian Football League, West Australian Football League or South Australian National Football League), technology, football and gym equipment, consultants and commercial licences (i.e., statistic providers) (Ryan, 2015). This high level of regularisation within the AFL is an interesting characteristic of the league, and a point of difference to many other professional sporting leagues around the world. As a result, professional AF organisations need to carefully consider how to best use their resources to maximise their competitive advantage (Gray & Jenkins, 2010). This is turn has significant implications on the relative value of organisations relying on objective decision support applications, such as the approaches taken in this thesis.

1.3 Outline of research structure

This thesis consists of seven chapters. Chapter One introduces the problem, and provides a justification for the thesis. It also provides some context for the sport of AF, which is the main focus for this thesis. Chapter Two provides a review of the literature that encompasses relevant research and its application within both AF and the broader team sport field. Chapter Three is the initial study of the thesis, and assesses the validity of the AFL Player Ratings metric. This study also serves to outline the suitability of the AFL Player Ratings metric for use as an objective measure of player performance for use in further studies. Chapter Four is the second study in the thesis, and focuses on support for short-term organisational decisions (i.e., those based on within season player performances). Chapter Five is the third study, and targets longer-term decision support, where multiple seasons of data are analysed. Chapter Six is the concluding study, and is an overarching study which compares both subjective and objective measures of player performance. Finally, Chapter Seven summarises the findings of this thesis and outlines practical applications from each of the studies undertaken. Further, it stipulates the future directions of research into modelling player performance data for organisational decision support in team sports.

CHAPTER TWO – LITERATURE REVIEW

Chapter Overview

Chapter Two provides an overview of the literature relevant to the research contained in this thesis. Each section will introduce its relevance to the thesis and then provide a summary of the related literature.

This chapter contains sections outlining the literature relevant to AF (section 2.1), performance data in team sport (section 2.2), as well as operations research and decision support systems in team sports (section 2.3). Further sections include the literature relevant to statistical models and machine learning in sport (section 2.4), longitudinal research in team sport (section 2.5), as well as quantifying the individual in both team sports (section 2.6), and specifically in AF (section 2.7).

2.1 Australian Rules football

The sport of AF has evolved since its initial inception in the late 1850's (Braham & Small, 2018; Norton, 2016). Over the course of its history, there has been a continual change in the gameplay and tactics (Norton, 2016; Norton, Craig & Olds, 1999; Woods, Robertson & Collier, 2017). There have also been various rule changes (Gray & Jenkins, 2010), providing opportunities for researchers to identify new tactical concepts and measures. In addition to these continual developments, there has been an increase and improvement in data availability and technologies associated with creating performance data in AF, which has further provided various avenues for associated research (Gray & Jenkins, 2010). Further, the implementation and ongoing expansion of the elite women's competition, the AFLW, has and will continue to bring further opportunities for research and the applied utilisation of player performance data in the sport of AF (Black et al., 2019; Clarke et al., 2018; Cust, Elsworthy & Robertson, 2018; Cust, Sweeting, Ball, Anderson & Robertson, 2019).

In AF, the majority of research undertaken to date which has modelled player performance data has focused on either the ability to explain match outcome (Cust et al., 2019; Robertson, Back & Bartlett, 2015; Robertson et al., 2016; Young, Luo, Gastin, Tran & Dwyer, 2019), or identify predictors of individual player performance (Tangalos, Robertson, Spittle & Gastin, 2015; Woods, Raynor, Bruce, McDonald & Collier, 2015). Furthermore, there have been various studies investigating the physical requirements and movement demands of the game (Clarke et al., 2018; Gray & Jenkins, 2010; Piggott, McGuigan & Newton, 2015; Ritchie, Hopkins, Buchheit, Cordy & Bartlett, 2016), leading to the development of systems to improve the specificity of training drills (Corbett et al., 2018), and to better comprehend collective team behaviour (Alexander, Spencer, Mara & Robertson, 2019; Alexander, Spencer, Sweeting, Mara & Robertson, 2019). Similarly, rule changes such as the numerous adjustments to the player rotation limits (third interchange player introduced in 1994, fourth interchange player introduced in 1998, three interchange players and one substitute introduced in 2011, four interchange players reintroduced in 2014 with a limit of 120 rotations, four interchange players with a limit of 90 rotations introduced in 2016), has prompted research into gaining a better understanding of the physical activity demands experienced by players, allowing for evidence-based changes in strategic match play and player rotation strategies (Dillon, Kempton, Ryan, Hocking & Coutts, 2018; Montgomery & Wisbey, 2016; Mooney, Cormack, O'Brien & Coutts, 2013).

2.2 Performance data in team sport

Performance data in team sport is continually evolving (Sarmento et al., 2014). Novel aspects of performance are continually being added to the already extensive set of tactical performance measures which are collected in professional team sports (Rein & Memmert, 2016). Additionally, improvements in technology has seen a concurrent increase in the accuracy of how performance indicators are reported (Carling, Reilly & Williams, 2008). In the majority of team sports, specifically invasion team sports, it is evident that not all players are subject to the same constraints, which through the analysis of generic performance indicators may be seen to enhance or hinder certain individuals contribution to the overall success of their team (Vilar, Araújo, Davids & Travassos, 2012). These constraints change for each different sport and can be conceptualised as specific match conditions relating to the particular individual, their task or their environment (Newell, 1986). The awareness of these constraints has allowed for professional sporting organisations to align their practices with theories common to skill acquisition (Woods, Jarvis & McKeown, 2019). An example of how this has shaped processes in professional sporting organisations is through improving representative designs of practice environments (Browne, Sweeting, Davids & Robertson, 2019; Corbett et al., 2018). An increased collection and analysis of performance data at training sessions can lead to an improved understanding of the specificity of particular drills to match play. This in turn allows for training activities to be designed to offer a closer representation of the behaviours during a match (Corbett et al., 2018; Woods et al., 2019).

The increase and improvement of performance data over the past decade is largely due to the to progress made in the development of player tracking technologies (Rein & Memmert, 2016). These technologies are used to estimate an athlete's position relative to the coordinates of the playing area. The resultant data can then be used to calculate measures of displacement, velocity and acceleration over a given epoch (Aughey, 2011). As such, it is now conventional practice for professional sporting leagues to collect performance data on both the what (technical performance indicators) as well as the where (spatiotemporal parameters), when (match time considerations), and why of performance actions (Gonçalves, Figueira, Maçãs & Sampaio, 2014; Stein et al., 2017).

Various studies within the team sport notational literature refer to the phenomenon of 'big data' and its potential impact on the future of performance and tactical analysis in team sports (Rein & Memmert, 2016). Typically, the term big data is associated with the volume, variety and velocity of data (Noor, Holmberg, Gillett & Grigoriadis, 2015). However, the term veracity has also been associated with the expression (Buhl, Röglinger, Moser & Heidemann, 2013; Stein et al., 2017). Within the context of performance data in team sports, the volume of data is related to the magnitude; in which there has been continual increase (Barnes, Archer, Hogg, Bush & Bradley, 2014; Bush, Barnes, Archer, Hogg & Bradley, 2015). This rise has seen performance data become more detailed, specific and collected on a wider range of players (i.e., at semi-professional, amateur and elite junior levels) (Bush et al., 2015). The variety of data refers to the different sources and formats in which data is captured and utilised (Rein & Memmert, 2016). Some examples of the different sources of data in applied team sport settings includes, performance indicator counts, positional data, anthropometric data, video capture, as well as both health and psychological records. The format of these data sources can vary from structured (i.e., clear predefined schema describing the data) to unstructured (i.e., data which lacks a definite schema) (Rein & Memmert, 2016; Sint, Schaffert, Stroka & Ferstl, 2009). The velocity of data relates to the speed at which the data is being generated (Rein & Memmert, 2016). Improvements in technology have allowed for large amounts of data to be generated in real-time (Hutchins, 2016). Thus meaning that raw data, as well as applications generated from this data can be available for coaches and analysts almost instantaneously. Lastly, the veracity of data relates to the uncertainty in the data (Stein et al., 2017). Specifically, as the volume, variety and velocity of the data all increase, the challenge of adequately managing the uncertainty in the data will evidently increase to ensure there is not a reduction in the quality of the data. In addition to the increase in the volume, variety, velocity and veracity of data that has come about, many of the data sources are becoming more valid and reliable (Di Salvo, Collins, McNeill & Cardinale, 2006; Rampinini, Coutts, Castagna, Sassi & Impellizzeri, 2007), as well as more readily available (Rein & Memmert, 2016; Stein et al., 2017).

As mentioned above, some of the biggest improvements in performance data is largely due to the progress made in the development of player tracking data. Sarmento et al. (2014) outlined that in recent years Global Positioning Systems (GPS) have improved to the extent that the data obtained is now of adequate enough to satisfy scientific standards. GPS triangulate location through the measurement of time it takes radio signals to travel from multiple satellites to a GPS receiver (Aughey, 2011). There has also been an improvement in the quality of Local Positioning Systems (LPS), for use in indoor stadiums (Hoppe, Baumgart, Polglaze & Freiwald, 2018). LPS differ to GPS in that radio-frequency is used to determine location by positioning anchor nodes around the playing area (Hedley et al., 2010). Although player tracking technologies are widely used in today's professional sporting competitions, GPS technology was only introduced into the AFL during the 2005 season, and a limit was set for each team, allowing five players per game to be monitored (Gray & Jenkins, 2010). This number increased from five to ten players per team in the 2009 season (Gray & Jenkins, 2010). Despite many studies outlining mixed results regarding the accuracy and reliability of GPS and LPS technologies to measure both total distance and velocity in field sports (Buchheit et al., 2014; Hoppe et al., 2018; Rampinini et al., 2015); much of the research conducted in these sports, including AF, still utilises these technologies to measure the movement demands and physical load of team sport athletes for purposes such as training prescription and design (Corbett et al., 2018; Cust et al., 2018). The improvement in player tracking technologies is not only limited to GPS and LPS technologies. In 2013, the National Basketball Association (NBA) implemented vision based tracking systems into all main stadiums to capture the two-dimensional location of players and three-dimensional location of the ball, allowing for recognition of specific actions, such as shots (Cervone, D'Amour, Bornn & Goldsberry, 2016; Minto, 2016). Vision based tracking systems work by inputting camera footage into computer vision software to extract positional data (Sherman & Craig, 2003). In comparison the GPS and LPS, vision based systems have the advantage of not requiring athletes to wear devices to monitor location (Craig, 2013). The advances of player tracking technologies have also allowed for an improvement in the development of various other types of performance data. For example, it has prompted an improvement in some objective player performance rating models, by including further positioning dynamics to more accurately assess the value of actions (Gonçalves et al., 2014; Memmert, Lemmink & Sampaio, 2017). Additionally, it has allowed for an improved understanding of collective team behaviour (Alexander, Spencer, Mara, et al., 2019; Alexander, Spencer, Sweeting, et al., 2019; Gonçalves, Marcelino, Torres-Ronda, Torrents & Sampaio, 2016; Travassos, Davids, Araújo & Esteves, 2013).

Outside of player tracking technologies, there have been various other improvements prompting further development of performance data in team sports. Many of these developments are similarly associated with improvements in technology. Specifically, the development of computer vision technology has had an impact on the ability to accurately capture the biomechanical movements of athletes (Giblin, Tor & Parrington, 2016). Developments in smartphone and tablet technology has allowed for improvements in the velocity of data, whereby complementary computer software packages can be used by practitioners to improve the opportunities for live data collection (Giblin et al., 2016). Similarly, these portable technologies have allowed for additional opportunities for remote athlete data collection (i.e., wellness data) (Giblin et al., 2016).

With the ongoing development of performance data in team sports, there are various avenues which can continue to be explored in the area of modelling player performance data. Specifically, the development of the official 'AFL Player Ratings' (outlined in further detail in section 2.7.3), has allowed for the studies in this thesis to explore how player performance can be modelled from the perspective of how much a player improves the field equity for their team. The following sections of this review will discuss the relevant literature regarding how the performance data in team sport is analysed and used by both researchers and applied sport scientists/analysts.

2.3 Operations research and decision support systems in team sports

Operational research is the application of statistical methods to problems of making decisions (Marlow, 2013). There has been considerable literature that targets tactical and strategic applications of operational research in individual and non-continuous team sports. Some examples include assessing the performance of professional tennis players by analysing the efficiency of their game (Ruiz, Pastor, & Pastor, 2013), evaluating performance of golfers by identifying areas of inefficiency (Fried, Lambrinos, & Tyner, 2004), as well as determining optimal batting orders (Swartz, Gill, & Beaudoin, 2006) and player selection (Barr & Kantor, 2004) in cricket.

In addition, there have also been applications to continuous team sports. In basketball, Cooper, Ruiz, and Sirvent (2009) used a data envelopment analysis to show the value of operational assessments of players in basketball, and how they could be implemented in place of classical indexes. This methodology allowed them to weight performance factors relative to their importance for each playing position. This resulted in an assessment of the effectiveness of player performance with respect to the specific characteristics of their position, as well as an evaluation relative to other assessed players. Also in basketball, Moreno and Lozano (2014) assessed the efficiency of NBA teams throughout the 2009-2010 season using both conventional and network data envelopment analysis approaches. Using these methodologies, this study was able to uncover sources of inefficiency within certain team's performance styles.

Although the concept of decision support seems inherent, the term's meaning and how it is used differs depending on the context (Bohanec, 2001). In this thesis, decision support refers to the utilisation of all available and relevant data to conduct structured, mathematically based approaches to decision-making (Morrison & Moore, 1999). The concept of decision support is often coupled with decision support systems (Bohanec, 2001), which are computerised information systems used to support decision-making and problem solving processes (Shim et al., 2002). Decision support systems evolved from a variety of areas of research; one area specifically being organisational decision-making (Shim et al., 2002). Research in this area has predominantly concentrated on improving the efficiency and effectiveness of decision-making through the use of information technology (Pearson & Shim, 1995; Shim et al., 2002). Within a team-based setting, the application of decision support is based on the notion that rarely will one individual be simultaneously the strongest in all areas of performance assessment (Belton & Stewart, 2002). Further to this, it is established that humans are susceptible to various biases in decision-making, and have limits to the amount of information they can comprehend (Grove, Zald, Lebow, Snitz & Nelson, 2000; Miller, 1956). Various studies in the team sport notational literature have supported these notions, as well as the adoption of decision support systems in applied sporting organisations, by drawing links between theories of cognitive limitations and decision-making (Raab, Bar-Eli, Plessner & Araújo, 2018; Robertson & Joyce, 2019). An example of this is bounded rationality, which suggests that in complex situations an individual's ability to make optimal decisions is constrained by both cognitive and environmental factors (Raab et al., 2018; Robertson & Joyce, 2019; Simon, 1957). Some examples of the cognitive factors include the aforementioned susceptibility to biases in decision-making, and the limitations to information processing capacity (Robertson & Joyce, 2019). Environmental factors include the constraints to time and resources available to the decision maker (Robertson & Joyce, 2019). By acknowledging these constraints, decision support systems can be utilised to provide contrasting objective evidence as to why certain factors/variables may be more valuable to team performance.

In many sports, team selection and talent identification processes are predominantly a subjective issue involving commonly accepted notions, different heuristics and past experiences to select and form a well-balanced team (Ahmed, Deb & Jindal, 2013). Despite this, decision support systems have been previously applied within a sporting context for team selection and talent identification purposes. Calder and Durbach (2015) used decision support systems to identify both performance levels in rugby players and the implied trade-offs that occur when selecting certain players over others. Additionally, the authors emphasised that the aim of using a decision support system was to provide a structured framework to support coaches in their decision-making process, not replacing the process all together. In basketball, Ballı and Korukoğlu (2014) used a decision support system to assist with the selection of junior basketball candidates. By applying the quantitative physical attributes and qualitative technical skills of the candidates, they were able to establish a model that objectively ranked the candidates relative to weightings given for each attribute and skill. In gymnastics, Pion, Hohmann, Liu, Lenoir, and Segers (2016) modelled the results of a multidimensional talent identification assessment, to use as a support mechanism for reducing the risks and costs associated with talent identification and development. Through utilising predictive models to analyse the results of the multidimensional talent identification assessment, rather than using coaches subjective impressions of these results, Pion et al. (2016) found that they could both reduce the risk of overlooking high potential gymnasts during the talent identification process and lower the financial costs of talent development. A further example includes Boon and Sierksma (2003) developed a decision support system in order to determine optimal player line-ups in volleyball, including both starting positions and rally positions relative to the individuals on the court.

The recurring suggestion from the literature (Ahmed et al., 2013; Bhattacharjee & Saikia, 2014) indicates that having objective models created from player performance data available to support decisions such as team selection and player recruitment is beneficial, but should not be completely relied upon. Rather, a balance should be found by utilising both objective and subjective criteria (Pappalardo, Cintia, Pedreschi, Giannotti & Barabasi, 2017). The research questions outlined in this thesis were focused on aligning with these suggestions. The studies conducted follow study designs similar to that in this existing literature, whilst emphasising a specific focus on utilising the methodologies and results as objective decision support tools, rather than decision making tools. Although the outcomes of this thesis do not intend to develop automated decision support systems, it is important to emphasise the importance of utilising relevant data and appropriate methodologies as objective support tools for organisational decisions, as opposed to basing decisions solely on subjective notions.

As outlined in further detail in the subsequent section, another important consideration with the modelling and analysis of performance data, is the interpretability for the user. As such, an important tool of decision support systems is the ability to effectively visualise and conceptualise the data, in order to convey a clear overview of the crucial information required to assist key decisions makers in their decision-making processes (Legg et al., 2012; Stein et al., 2017).

2.4 Statistical models and machine learning in sport

With the rise in both detail and quantity of available performance data in elite team sports, has come an increase in popularity of applying statistical models and machine learning methodologies to analyse and interpret team sport performance data (Rein & Memmert, 2016). This includes a range of linear and non-linear techniques, each which serve various purposes within team sport performance analysis (Robertson, Back, et al., 2015). Specifically, many non-linear machine learning methodologies are becoming ever more prevalent in the team sport notational literature due to their ability to identify multiple patterns in data between predictor variables and outcome variables (Dutt-Mazumder, Button, Robins & Bartlett, 2011).

One of the main considerations with the analysis of performance data in team sport, is ensuring that repeated measures data is treated appropriately (Hopkins, Marshall, Batterham & Hanin, 2009). Specifically, when values are measured repeatedly (i.e., round-to-round, or season-to-season) on the same individual (or the same team), they are typically more similar than that of values from different individuals (or teams). As such, these values are usually more positively correlated and are therefore not considered independent (Schober & Vetter, 2018). Failure to account for repeated measures can result in standard errors being underestimated, falsely leading to more significant results (Schober & Vetter, 2018; Williamson, Bangdiwala, Marshall & Waller, 1996). Some statistical models and machine learning methodologies can account for this in the modelling process, however, many algorithms assume independence between observations (Lusher, Robins & Kremer, 2010; Robertson, Bartlett & Gastin, 2017). If the intent of the research is not to assess longitudinal changes, then a simple summary statistic approach can be used to account for the repeated measures (i.e., calculate the mean for each player across a season) (Albert, 1999). One alternative to avoid this assumption is to develop separate models for each of the repeated measures (i.e., separate models for each individual or team) (Bartlett, O'Connor, Pitchford, Torres-Ronda & Robertson, 2017). In addition to repeated measures data, due to this assumption of independence between observations, analysis methodologies also need to account for any variables with collinearity (Dickinson & Basu, 2005; Vetter & Schober, 2018). For example, the variables age and playing experience are outlined later in this thesis, which are shown to have a strong positive correlation. As such, the variables were analysed separately.

Another important consideration is the interpretability of specific models/methodologies, and their suitability to both answering the research question, and subsequently implementing the findings within a professional setting. Whilst some particular methodologies often lead to well-fit and more accurate outcomes, this often comes at the cost of a lack of interpretability (Johansson, Sönströd, Norinder & Boström, 2011). As such, there is often a trade-off between improved accuracy and improved interpretability (Johansson et al., 2011; Ofoghi, Zeleznikow, MacMahon & Raab, 2013). For example, improved accuracy may potentially be more suitable for purposes such as outcome prediction, however, if the research focus is more centred on the explanation of outcomes, improved interpretability may be preferred (Morgan, Williams & Barnes, 2013; Robertson, Back, et al., 2015).

There are two distinct variants of machine learning: supervised and unsupervised methods (Figure 2.1). Supervised models are created with both input data and anticipated outputs (i.e., gives player performance data and the actual output). Once trained, the model then uses all the input data to approximate the relationship between input and specified outputs (Love, 2002). On the other hand, unsupervised models are created with only input data; allowing the model to learn the structure of the data without specifying output variables (Love, 2002).

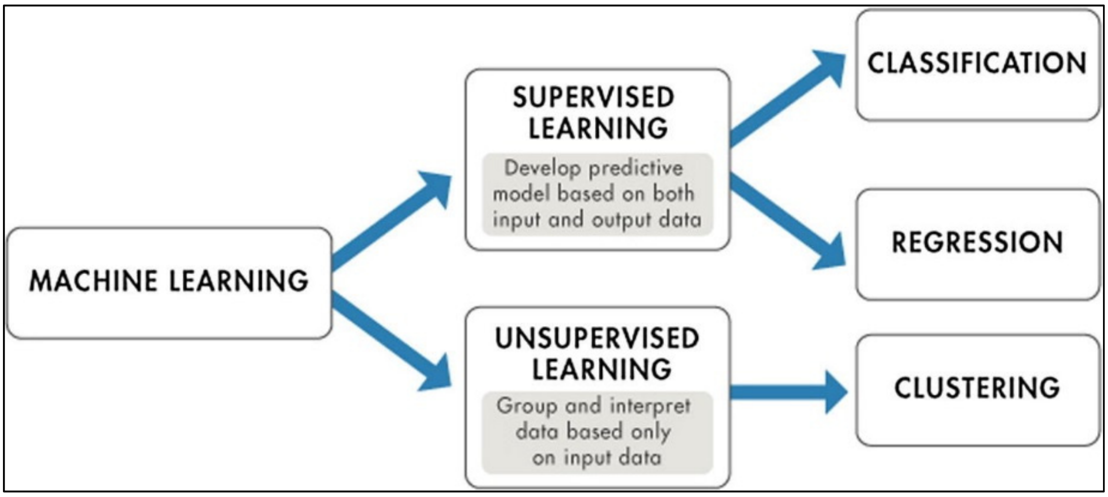

Figure 2.1 Supervised learning versus unsupervised learning (Mathworks, 2017).

A vital step within the development of supervised models is training and testing the model, or cross-validating of the model. The basic notion of these processes involves building the model on a proportion of the data, and then testing its accuracy, or ability to predict the outcomes on the remaining proportion (Bunker & Thabtah, 2019). This process promotes the construction of a balanced model, and reduces the likelihood of the model being overfit to the specific dataset (Rokach & Maimon, 2008). The term overfit (or overfitting), refers to when a model is constructed to be overly specific to the current dataset, rendering itself potentially less generalisable to providing predictions/explanations with new data (Morgan et al., 2013; Rokach & Maimon, 2008). Though there are various processes for doing this, it is important that for models using longitudinal performance data that the method chosen maintains the order of the data (Rokach & Maimon, 2008). This is vital to ensure the created model is only testing its accuracy based on data available beforehand only (i.e., if a dataset contains data from multiple years, it is important to include data from earlier years as part of the training set, and then data from later years as the test).

Outlined in the following subsections is a review of the more commonly used statistical models and machine learning methodologies in the team sport notational literature, and their use to modelling player performance data. The models and methodologies used within the studies contained in this thesis (Chapters Three to Six) are outlined initially and in more detail. These are then followed by some of the other commonly used models and methods in the team sport notational literature.

2.4.1 Supervised learning

2.4.1.1 Regression models

Regression models look to estimate the relationship between dependent and independent variables (Lindley, 1990). Specifically, they look to explain the changes in a dependent variable in relation to changes in independent variables (Draper & Smith, 1998). Regression analyses have the advantage of being extremely flexible, in that there are many variants (i.e., linear, logistic, polynomial) (Draper & Smith, 1998). However, one of the main drawbacks of is the amount of specific assumptions that need to be taken into account (Draper & Smith, 1998). For example, a linear regression analysis assumes the data has no heteroscedasticity, no outliers and assumes independence between variables (Draper & Smith, 1998).

Despite these assumptions, regression models have been used extensively in the notational team sport analysis. Some examples of how they could be used for decision support of factors with a continuous dependent variable includes Gómez, Silva, Lorenzo, Kreivyte and Sampaio (2017) who used multiple linear regression to identify the effects of player substitutions in elite basketball, in relation to coach-controlled, on-court and situational variables. Applications of their findings could provide a greater understanding of the effects and timing of specific substitutions, and could help to improve the substitution pattern of players. Hoppe, Slomka, Baumgart, Weber and Freiwald (2015) used a stepwise multiple linear regression analysis to determine the association between match running performance and seasonal success in elite European soccer teams. Their main finding indicated that total distance covered with ball possession was a positively associated indicator, and could be used as a new key indicator for achieving season long success.

Alternatively, some examples of other regression models includes Gramacy, Jensen and Taddy (2013) who used a logistic regression model to estimate the effects of individual players on team goal scoring in ice hockey. Model applications were used to evaluate individual player contributions, allowing for considerations to be made about a player's value, and how to optimise player match-ups and team lines. Leicht, Gómez and Woods (2017) used a logistic regression to identify a unique combination of performance indicators which could explain match outcome in 85.5% Olympic men's basketball matches. These results could be used within an applied setting to provide coaches with the capability to devise match strategies to improve their likelihood of winning. Woods, Sinclair and Robertson (2017) used an ordinal regression analysis to support the results of a classification tree model. The analysis found a unique combination of performance indicators providing an explanation of ladder position in rugby. The practical applications of their study outlined that the findings could be used by coaches and analysts to develop game strategies and to assist with the implementation of practice conditions that could increase their teams' likelihood of success.

Regression models have also been commonly used in AF. Specifically, they have been used for talent identification purposes, such as to predict draft selection or playing status of elite and sub-elite juniors, based on physiological and anthropometric attributes (Robertson, Woods &

Gastin, 2015; Woods et al., 2015). Further use has centred around assessing team and individual player performances from physical capacity and movement variables (Hiscock, Dawson, Heasman & Peeling, 2012; Piggott et al., 2015). Alternatively, Robertson, Back, et al. (2015) assessed the relationships between team performance indicators and match outcome, suggesting that the findings could be useful in informing strategy and game plan development.

In addition to traditional regression models, is a segmented model (otherwise known as a piecewise linear model). Segmented models are an extension to linear regression models, which examine the data to identify whether two or more fits more accurately explain the data trend (Fransen et al., 2017). Despite minimal use in the team sports notational literature, these have been particularly useful to explain when dependent variables show sudden changes in their response to the predictor variable/s (Fransen et al., 2017). Some specific uses include Fransen et al. (2017) who used a segmented model to identify periods of improving and declining development of both motor competence and physical fitness in high level youth soccer players. Alternatively, Woods, Robertson, et al. (2017) utilised a segmented model for a more holistic purpose, by attempting to identify specific points in time where the AFL has seen an evolution in game-play, highlighted by significant shifts in team performance indicator characteristics. Segmented models were employed in the study outlined in chapter five of this thesis. This particular model was utilised in this study as a complementary analysis to a linear model, in order to identify if and where changes in the trend of the data occur longitudinally.

2.4.1.2 Decision tree learning

Decision tree models are used to analyse both linear and non-linear data, can be used for both classification and regression problems, and can handle either categorical and continuous data variables (Gupta, Rawat, Jain, Arora & Dhami, 2017). The trees divide data predictors into mutually exclusive subsets of nodes that best describe the outcome of the dependent variable (Kass, 1980).

Various types of decision trees exist, each of which use different statistical measures to identify how and where the tree splits (Gupta et al., 2017). Depending on the model, trees can split at the decision nodes as either binary or non-binary (multiway); where at each decision node there is either two, or more than two branches, respectively, which split into either further decision nodes, or a terminal node (Antipov & Pokryshevskaya, 2010). Figure 2.2 outlines the basic structure of a decision tree.

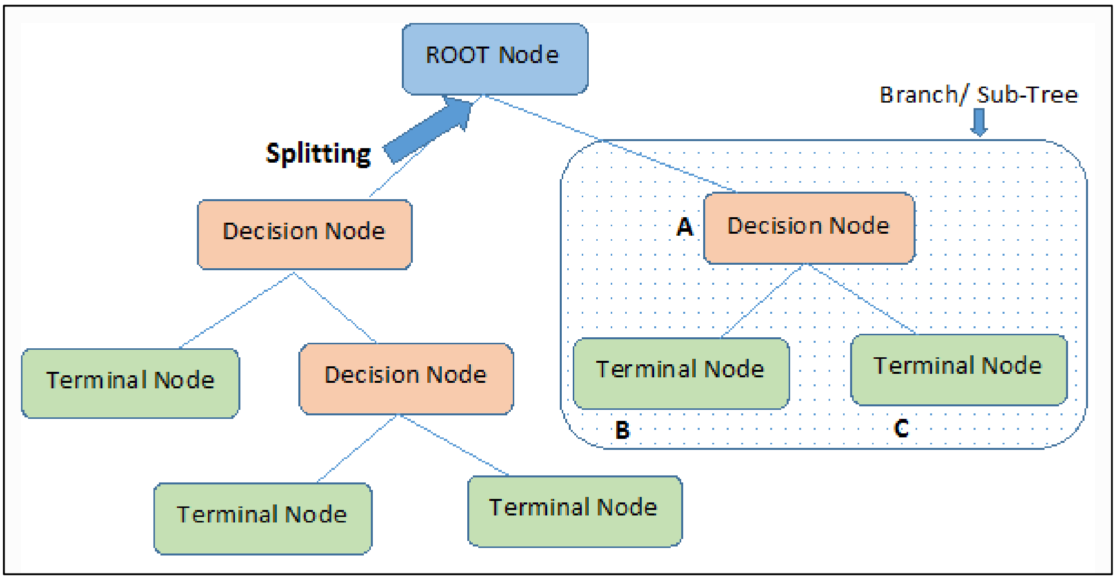

Figure 2.2 Basic structure of a decision tree (Jain, 2017).

The primary benefits of decision tree analyses are their ability to analyse both categorical and continuous data, to identify non-linear trends and to handle outliers (Morgan et al., 2013; Robertson, Back, et al., 2015). A further benefit of their use in an applied setting is the ease of visual interpretation by lay audiences, making them practical for use for decision support in an applied setting (Robertson, Back, et al., 2015; Robertson, Woods, et al., 2015). On the other hand, the main limitation of decision tree analyses are that they do not take into consideration the dependency of observations (Hopkins et al., 2009).

Two of the more commonly used models within the team sport notational literature are chi-squared automatic interaction detection (CHAID), and classification and regression tree analyses (CART). CHAID analyses build non-binary trees using the chi-squared statistic to denote the importance of each independent variable (Antipov & Pokryshevskaya, 2010; Kass, 1980). For categorical variables, there will be a subset of separate nodes for each variable within the category. For continuous data, nodes are expressed as a range (i.e., example range could be from 1 to 100, where nodes could be split [1-25], (25-50], (50-75] and (75-100]). For both categorical and continuous, each subset consists of two or more nodes, and displays the predicted outcome for each variable that falls within each variable/range. The model is created by finding the best partition for each feature, and then comparing each predictor to select the best one. For each node of this predictor, the remaining features are then re-analysed independently to further improve the model (Kass, 1980). On the other hand, CART analyses build binary trees using the Gini Index to select the splitting attributes (Breiman, Friedman, Olshen & Stone, 1984; Gupta et al., 2017). The level at which the attributes split are then determined by the value which maximises the agreement of further decision/terminal nodes with respect to the dependent variable (Antipov & Pokryshevskaya, 2010). Alternatively to CHAID, all features are then re-analysed independently to further improve the model.

Within the team sport notational analysis literature, decision tree models have been used in various different sports. Some example of applications includes Gómez et al. (2015), who used a CHAID analysis in basketball to predict the effectiveness of variables relating to an offensive screen, in order to better understand and anticipate responses to defensive actions. Pischedda (2014) used a CHAID decision tree as a prediction tool forecast the match outcome of ice hockey matches using traditional and advanced statistics. Additionally, Morgan et al., (2013) used a binary splitting decision tree to determine the predictive attributes of one-on-one game play in field hockey, identifying that speed difference between attacker and defender was the most important feature determining the outcome.

In AFL specifically, Robertson, Back, et al. (2015) used a CHAID analysis as a non-linear alternative to binary logistic regression to assess the relationship between performance indicators and match outcome in the AFL. The findings from these relationships outline both technical and tactical applications which could be utilised by coaches and player development staff within AF clubs. Specifically, an understanding of the performance indicators most important to match outcome provides insight into the areas of the game that should be targeted during training sessions.

A similar alternative to decision trees are decision lists. Decision lists share many of the similarities to decision trees, however decision lists have an inherent order, whereby the rules are trialled in a linear manner (Fürnkranz, 2017; Rivest, 1987). As an example, if the response to the first decision rule is 'true', it renders an outcome variable; if the decision is 'false', it renders a new rule that removes all responses covered by the previous rule/s (Fürnkranz, 2017). Unlike decision trees, decision lists have been scarcely used within the team sport notational literature. One specific example includes that by Woods, Veale, et al. (2018) who used a decision list to generate a set of rules to classify talent identified junior players into playing positions based upon technical performance indicators.

Throughout this thesis, a decision tree or decision list analysis was conducted in three of the four studies (chapters three, four and six). These models were employed in these studies due to their versatility to analyse both categorical and continuous data, their ability to identify non-linear trends as well as, their ease of visual interpretation, making them practical for use in an applied setting.

2.4.1.3 Mixed effects models

Mixed effects models have been frequently used in team sport research, and are most commonly used to model performance trajectories of individuals or teams, as they allow for the explanation of a performance outcome through a combination of fixed and random effects (Cnaan, Laird & Slasor, 1997). Fixed effects are factors that are seen to affect the entire group of subjects to the same extent (Cnaan et al., 1997). Conversely, random effects are factors whose levels are seen as random, and affect the population to different extents. It is these random effects which account for the repeated measures in mixed models (Cnaan et al., 1997). There are various advantages to using mixed models for analysing performance data in team sports. Specifically, using a linear mixed effects model as opposed to other linear based analyses (i.e., regression or ANOVA) is that the incorporation of random effects improves the ability of the fixed effects to explain the dependent variable (Hopkins et al., 2009); thus better enabling our ability to describe how these fixed effects relate to outcomes (Schober & Vetter, 2018).

Some recent examples outlined in the team sport notational literature include Kempton, Sirotic and Coutts (2017) who used a linear mixed model to examine differences in physical and technical performance profiles of individual rugby league players, in order to determine the effect of each performance variable. Physical performance variables and team identity were set as fixed effects, whilst individual player identity was set as a random effect to account for the dependence arising from repeated measurements. Results of the study indicated that the main factors differentiating between successful and unsuccessful teams was proficiency in technical performance components and defensive actions. Castellano, Blanco-Villaseñor and Alvarez (2011) used a multivariate mixed model to assess physical performance profiles in elite soccer match-play. Using contextual variables such as match location and opponent quality, as well as considering the two halves of a match and the partial or final result, the model looked to determine whether these effects displayed differences in the physical demands of a match. Applications of the findings indicated that training designs constructed from competitive physical demands of match performance should consider each of these factors in conjunction with one another, and should be considered with respect to effective playing time, as opposed to total match time. Alternatively, Casals and Martinez (2013) employed a linear mixed model to assess player performance in basketball, by considering match performance indicators and accounting for the repeated measures of individual players. The research outcomes were twofold, whereby they produced a model to quantify the relative contributions of individual players with respect to team performance, as well as highlight the variables which had the largest effect on their variability between players.

Mixed effects models have also been used in AF research. Specifically, they have been used recurrently to assess the effects of physical load across a season to account for repeated measures. Examples include Ritchie et al. (2016) who utilised a linear mixed model to quantify the training and competition load of elite AF players, whilst accounting for between-player effects and distinctive periods across a full season. Montgomery and Hopkins (2013) also used a linear mixed model to determine the effect of combined game and training loads on muscle soreness across the immediate days following a load. A random effect was similarly used to account for the repeated measures of individual player across the season. The applications of the findings from these studies could provide valuable information to professional sporting organisations by identifying ideal periods of loading and unloading at various stages of the week and season. The inclusion of player identity as a random effect allows for the prescription of periodised training loads at both a team and an individual player level.

Mixed effects models were employed in the third and fourth studies of this thesis (outlined in chapters five and six). These models were utilised in these studies in order to control the variability created by the repeated measures on specific players. This turn allowed for improvements in the ability of the fixed effects to explain the dependent variable (player performance, as outlined by player rating metrics).

2.4.1.4 Other supervised statistical models and machine learning methodologies

Generalised estimating equations (GEE) is a statistical analysis technique which has been used to determine the association of performance indicators on longitudinal team and individual performance. GEE is an extension of the generalised linear model, and was first used by Liang and Zeger (1986) as a method of analysing longitudinal data. Within team sport analysis, GEE is particularly useful as it allows for multiple observations (Hothorn & Everitt, 2006), thus allowing for comparisons between multiple seasons, between multiple teams in a competition or between each player within a team. Another strength of GEE analysis is that it can be used to model correlated longitudinal data, that has a non-normally distributed dependent variable (Hothorn & Everitt, 2006; Zeger, Liang & Albert, 1988; Ziegler & Vens, 2010). Despite the abovementioned benefits, GEE has been used scarcely in team sport within the sports literature. In AF, Robertson et al. (2016) used a GEE to construct a model explaining match outcome as a function of in game performance indicators. The GEE was used to determine a feature set of these performance indicators, whilst adjusting for the dependence of each team. In golf, GEE has been used to determine the validity of certain skill tests on player ability. Robertson, Burnett and Gupta (2014) developed a model to determine the association between skill test scores, and performance in competition. A further study by Robertson, Gupta, Kremer and Burnett (2015) used GEE models to determine construct validity, discriminant validity and predictive validity of multiple skill tests to ascertain the ability of elite and high-level amateur golfers.

Random forests algorithms use multiple tree predictors, each considering a random subset of known features in order to get a more accurate prediction (Breiman, 2001; Gonçalves, Coelho e Silva, Carvalho & Gonçalves, 2011). Like decision trees, random forests also work for both classification and regression problems. A strength of random forest algorithms is their ability to consider non-linear interactions between variables (Robertson, Spencer, Back & Farrow, 2019). Additionally, they have been highlighted as one of the most accurate learning algorithms available (Breiman, 2001; Gupta et al., 2017). However, the improved accuracy comes at the cost of being less simple to interpret (Gupta et al., 2017). Despite this, random forest algorithms have been frequently used in the team sport notational literature, with the predominant utilisation being for prediction (Lock & Nettleton, 2014; Zimmermann, Moorthy & Shi, 2013). Some examples of random forest use in the team sport notational literature includes Lock and Nettleton (2014) who used a random forest algorithm to determine the win probability prior to each play of an National Football League game. The outcomes of this analysis allow for support of in game decisions, such as whether to accept or decline penalties based on the current situation and the context of the game. Random forests have also been used to assess injury risk of team sport athletes, whereby a predictive model can been created and used as a decision support tool to strategically manage players most at risk of injury (Rossi et al., 2018; Talukder et al., 2016). Some specific examples in AF include Spencer, Morgan, Zeleznikow and Robertson (2016) who utilised a random forest algorithm to inspect the importance of the opposing team as a variable amongst other performance indicators when describing the outcome of match quarters. Robertson et al. (2019) used a random forest algorithm to develop a model to determine the influence of contextual constraints on kicking performance. Woods, Veale, et al. (2018) used a random forest algorithm to classify talent identified junior players into playing positions based upon technical performance indicators.

Discriminant analysis is another statistical model which has been applied to performance data in team sports. It is a linear classifying methodology, whose primary function is to classify levels of an outcome (McLachlan, 2004). Naturally, popular applications of discriminant analyses within the team sports notational literature have been to utilise game related statistics and performance indicators to differentiate between different match outcomes (Castellano, Casamichana & Lago, 2012; Gómez, Pérez, Molik, Szyman & Sampaio, 2014; Lago-Peñas, Lago-Ballesteros, Dellal & Gómez, 2010; Lago-Peñas, Lago-Ballesteros & Rey, 2011). A specific example of this is Gomez, Gasperi and Lupo (2016) used a discriminant analysis to identify which situational and tactical variables best differentiate winning and losing teams during the final quarter of closely contested NBA games. The findings of this study allow for a greater understanding of the closing stages of basketball games, and could be utilised to improve the specificity of training sessions. Alternatively, discriminant analyses have utilised game related statistics to differentiate between playing positions. In basketball, Sampaio, Janeira, Ibáñez and Lorenzo (2006) examined the differences in game related statistics between each position, with the intention of increasing the effectiveness of player recruitment processes through an awareness of important position specific player contributions to team performance. Another popular application of discriminant analyses has been to determine whether game related statistics and performance indicators can predict which level of competition players will be selected to play. An example of this includes Gabbett, Jenkins and Abernethy (2011) who used anthropometric and physiological attributes, as well as technical and perceptual skills to predict selection in professional National Rugby League.

Various studies have utilised discriminant analyses in the AF notational literature, such as that by Woods, Veale, et al. (2018), who used it as a linear alternative to both a random forest analysis and a Partial decision tree (PART) decision list. Using technical skill indicators, the discriminant analysis (and other analyses) demonstrated difficultly in accurately classifying playing position; indicating that talent identification practices should consider additional tailored technical skill indicators to objectively identify juniors with distinctive positional attributes. Further, Le Rossignol, Gabbett, Comerford and Stanton (2014) used a discriminant analysis to determine the importance of physical capacity and repeat sprint ability to team selection in elite AFL players.

2.4.2 Unsupervised learning

2.4.2.1 Clustering and other similarity-based methodologies

Clustering methodologies are a group of analysis techniques used to partition data into meaningful subgroups (Fraley & Raftery, 1998; Jain, 2010). These subgroups are organised relative to the similarity (or dissimilarity) between observations, and summarise key features of the data (Clausen, 2012). Similarly to decision trees, one of the strengths of clustering methodologies, particularly for use in an applied setting, is the ease of visual interpretation by lay audiences (Smoliński, Walczak & Einax, 2002). Clustering methodologies determine the level of similarity of observations through a measure of distance (i.e., Euclidean, Manhattan, Mahalanobis, Pearson). There are various types of clustering methodologies, however, the most prominent methodology within the team sport literature is the *k*-means method (Ofoghi, Zeleznikow, MacMahon & Raab, 2013). *K*-means is a partitioning method, whereby the number of subgroups is pre-specified (Jain, 2010). Cluster centres (i.e., centroids or means) are determined, and observations are then partioned according to the distance from these central points (Jain, 2010). Cluster centres are then re-determined by the mean of distances of all observations in the group, and then once again observations are re-partioned (Jain, 2010). This process is repeated until the group centres remain stable (Jain, 2010).

Some examples of the use of clustering methodologies from the team sport notational literature include Zhang et al. (2018) who used a combination of anthropometric characteristics and playing experience to cluster various types of NBA players. The authors used player technical and physical performances to outline a player's similarity to their cluster centroid. The results of this study provide an understanding of the influence anthropometric characteristics and playing experience have on the technical and physical performance of NBA player. The practical applications of this work could be used to assess team rosters, and guide player recruitment strategies. Another application of clustering includes that by Gyarmati, Kwak and Rodriguez (2014) who utilised both *k*-means and hierarchical clustering methods to evaluate the style of passing structures in European soccer teams. Using observations derived from flow motifs of each teams passing network, the cluster analyses outlined the similarities and differences between teams. The two methodologies illustrated similar trends, and each provide an example of how opposition team playing styles could be analysed in an applied setting.

Some example applications of clustering methodologies in AF includes Corbett et al. (2018) who used a *k*-means clustering algorithm to outline drill classifications relative to the physical and skill-related requirements. Two separate models were created for the physical and skill-related requirements, respectively, and each drill was assigned to a subgroup based on the proximity to the cluster centre. The outcomes of this research could easily be implemented within an applied setting in order to optimise team training sessions, through selection of drills which exhibit specific constraints of interest, and their specificity to match requirements. Another example includes that by Spencer et al. (2016) who also used a *k*-means methodology to cluster team performance across each quarter of a match, derived from a summary of performance indicators. Clusters were subsequently compared to score margin for each quarter to determine the success of cluster types. Team profiles were then developed from frequency in which they experienced each cluster type. The applications of this research could be used to assist with team game style design, as well as to assess team playing style of upcoming opponents.

Alternatively to clustering methodologies, various studies have been designed using just the distance measures to determine the levels of similarity between observations. Thus, instead of outlining the similarity of observations to subgroups, observations are outlined by their level of similarity to all other observations. An example of this type of methodology in AF is that by Jackson (2016b), who used vector angles to determine the similarity between all individual players across the AFL, based on the frequency of technical and contextual match involvements. The applications of this research could be used for recruiting purposes, in order to identify players with similar traits to that of other desired players who are unattainable. This concept of using distance measures to determine the levels of similarity between observations was also employed in the study outlined in chapter four of this thesis. Specifically, Euclidean distances were utilised to determine the level of similarity between player performance profiles.

Similarity based methodologies have also been used for supervised classification purposes, whereby knowledge about data subgroups is available prior to modelling. An example of this type of methodology in AF is that by Sargent and Bedford (2010) where players were grouped into pre-determined positional categories based 13 game related performance variables. Classification was determined through the calculated Mahalanobis distance from positional subgroup centroids. The applications of this research could be used to create more specific player evaluations, whereby a player's influence on match performance is assessed based on position specific elements.

2.4.2.2 Social network analysis

Social network analyses are another type of methodology which have become increasingly popular within the team sport notational literature (Passos et al., 2011; Young, Luo, Gastin, Lai & Dwyer, 2019). Social networks have been found to be a valuable tool for exploring and informing relationships within a team dynamic, based on the notion that team structural cohesion is positively related to team performance (Warner, Bowers & Dixon, 2012). As such, their application within sport has typically been to investigate intra-group interactions among sporting teams (Lusher et al., 2010). Specifically, they have commonly been used in soccer to identify the contributions of individual players to team performance (Clemente, Martins, Wong, Kalamaras & Mendes, 2015; Duch et al., 2010), and to measure the effect of network attributes on team outcome (Grund, 2012; Mclean, Salmon, Gorman, Stevens & Solomon, 2018). Additionally, social network analyses have been used to assess the strategic organisational processes of teams within basketball. For example, Clemente, Martins, Kalamaras and Mendes (2015) identified the centrality levels of tactical positions across various levels of basketball competitions. The network analysis outlined that irrespective of competition level, the point guard held the prominent tactical position during the attacking process, as was the central link between team members.

The use of network analyses in AF has been sparse. Sargent and Bedford (2013) used a network analysis to simulate player interactions within a team, and measured the effect of network attributes on final score margin. The results found that the measure of team centrality adequately predicted the match score margin; thus indicating that the findings could be applied to measure the contribution of players to the final margin. More recently, Young, Luo, Gastin, Lai, et al. (2019) used a social network analysis to determine whether characteristics of teamwork in AF are associated with team performance. The study found that whilst each AF team's network remained stable, there were differences seen in measures between teams. Additionally, the authors outlined that the tactical measures most indicative of successful match outcome included effective passes, team passing density and the average possession chain length. Another example includes Braham and Small (2018) who outlined various network properties as a proof of concept for the use of network analysis in AF. The findings of the study indicated that analysis of these measures can quantitatively distinguish different playing styles, providing insight into the structure and strategy of AF teams. Furthermore, the findings outlined that centrality measures were useful in predicting the outcomes of future matches, as well as analysing the contributions of individual players.

2.5 Longitudinal analysis in team sport

Longitudinal data analysis is commonplace within the notational team sport literature. There are various uses for longitudinal research studies in team sport, with the primary benefit being the ability to gain a greater understanding of how certain effects and factors change over time (Caruana, Roman, Hernández-Sánchez & Solli, 2015; Windt et al., 2018). A further benefit of longitudinal studies is that they usually increase the precision of the estimated effects (Mascha & Sessler, 2011; Schober & Vetter, 2018).

As with many of the statistical and machine learning approaches outlined in section 2.4, the outcomes demonstrated in many of the studies in this section have the ability to be used to support the decisions which professional sporting organisations face. By discovering patterns and extracting relationships between the studies variables, ideally the models can be used for further application to guide and support the decision-making processes. Specifically, they can be used to support the identification of top performers within the sport and their value, prompting the selection and recruitment of the most suitable players (Drikos & Tsoukos, 2018). Alternately, they can assist with the setting ideal performance standards, to manage athletes and teams more effectively (Drikos & Tsoukos, 2018).

The typical statistical analyses and machine learning methodologies used for longitudinal studies are those which account for repeated measures (Hopkins et al., 2009). In addition, there are various other considerations to be made during model selection and analysis of longitudinal data (Windt et al., 2018). Some examples include accounting for missing data (Collins, 2006), specifying which effects are considered between-person (i.e., age) as opposed to within-person (i.e., individual ability) effects, and determining which variables are considered time-varying (i.e., performance, physical load) as opposed to those which are stable (i.e., sex) (Windt et al., 2018).

One of the more prominent uses of longitudinal research in the team sport literature has been to analyse physical performance data to gain an understanding of physical load monitoring, with the intent to better understand injury risk. There have been numerous examples of this in AF (Carey et al., 2018; Colby, Dawson, Heasman, Rogalski & Gabbett, 2014; Colby et al., 2017; Murray, Gabbett, Townshend, Hulin & McLellan, 2017; Stares et al., 2018; Veugelers, Young, Fahrner & Harvey, 2016), as well as more broadly in other team sports such rugby league (Windt, Gabbett, Ferris & Khan, 2017), rugby union (Cross, Williams, Trewartha, Kemp & Stokes, 2016) and soccer (Ehrmann, Duncan, Sindhusake, Franzsen & Greene, 2016).

Further research has been applied on other quantitative measures, such as player performance ratings, measures of physical capacity and a player's market value. Additionally, these variables have been measured longitudinally on various time series including the age of an athlete, amount of years within a professional program, their match's experience, as well as timelines defined by the period from preparation to competition (i.e., seasonal for annual competitions, or a quadrennial period for Olympic sports) (Torgler & Schmidt, 2007).

Much of the research focused on measuring player performance longitudinally has looked to identify certain stages or trends in performance; namely identifying when athletes peak. Some examples of this include Dendir (2016) and Kalén, Rey, de Rellán-Guerra and Lago-Peñas (2019), who each looked to identify the age of peak technical performance in soccer, and how this age varies across the different playing positions using player performance ratings and market value, respectively. In addition to determining when this peak occurs, Kalén et al. (2019) were able to identify that a significant longitudinal shift in the peak age of athletes has occurred in the last three decades, seeing athletes peak between one-to-two years later. Similarly in baseball, both Bradbury (2009) and Fair (2008) investigated peak technical performance and the age effects of skills in baseball. Both studies found that different aspects of a player's performance peaks at different times relative to the athletic demands of a player's position and the associated roles that accompany this. Specifically, athletic skills such as running and pitching peak earlier, whilst skills based on experience and knowledge such as the ability to drawing walks, peak later.

In addition to these analyses conducted on the individual data, longitudinal studies have similarly been undertaken based on team performance. A prominent example of this is the inclusion of team-based rating models, such as ELO style rating models (Hvattum & Arntzen, 2010; Stefani, 2011). Despite a large proportion of research the on team-based rating models being geared towards match prediction and the ability to outperform betting markets (Carbone, Corke & Moisiadis, 2016; Lopez & Matthews, 2015; Ryall & Bedford, 2010), some studies have alternatively looked to evaluate things such as fixture difficulty (Josman, Gupta & Robertson, 2016), to objectively identify and measure the different playing styles of opposition teams (Gómez, Mitrotasios, Armatas & Lago-Peñas, 2018), and to improve the effectiveness of team management processes (i.e., team selection, team formation) by assessing the effect on changes to expected team performance (Dadelo, Turskis, Zavadskas & Dadeliene, 2014). Additionally, in Mangan and Collins (2016) development of a team-based rating system for Gaelic football, their recommendations for use were to be used as a team monitoring tool, allowing for coaches and management staff alike to review and support decisions relating to a team progress.

Another focus of team-based longitudinal studies has been to outline methodologies to create tactical and strategic periodisation strategies, whereby the outcomes of the research can be used to inform the planning and preparation of a team's schedule (Robertson & Joyce, 2015). By accounting for factors such as upcoming match difficulty, team form, days between matches and travel, team sport organisations can benefit from being able to optimally prepare for each stage of their competitive schedule, with the overall goal of team performance peaking at the point of specific competitive events (Robertson & Joyce, 2018). Some examples of this within the notational team sport literature include Robertson and Joyce (2015) who developed a match difficulty index in super rugby, allowing for development of improved specific tactical periodisation plans. Robertson and Joyce (2018) provided a similar application within professional AF, with the additional inclusion of updating match difficulty indexes monthly in-season, in order to gain a better understanding of the influence of each factor, and if/how they vary as the season progresses.

2.6 Quantifying the individual in team sports

Within the elite competitions of many invasion team-based sports, an increase in the collection and reporting of performance data has led to the existence of more detailed and comprehensive performance rating systems in both the literature, and applied sport science (Hutchins, 2016). Specifically, a portion of this literature has undertaken detailed analyses relating to a player's individuality, value and potential. When these type of analyses have been undertaken in individual sports, typically the match/race result has been used as an objective outcome to directly compare against performance (McHale, Scarf & Folker, 2012). This approach has similarly been used in team sports such as baseball, where individual performance has been objectively quantified as a result of direct player actions (Chao-Chien, 2014; Streib, Young & Sokol, 2012). However, within invasion team sports such as AF, soccer and rugby, developing rating systems is much more complex due to the absence of objectively quantifiable outcomes that emanate directly from player actions (Gerrard, 2007). Specifically, the dynamic nature, varied individual roles and complex interactions which exist between individuals contribute to the complexity in these sports (Radovanović, Radojičić, Jeremić & Savić, 2013; Robertson, Back, et al., 2015). Despite this, there have been various studies look to quantify individual performances within team sports. Many of these studies have utilised the aforementioned statistical models and machine learning methodologies in their analyses. Typically, studies looking to quantify individual player performances are conducted for applied purposes including talent identification or player performance evaluation/valuation. In most cases, these systems propose to encapsulate player performance on a quantitative scale, to allow for ease of use.

Some examples from the team sport notational literature include Duch et al. (2010), who used a network analysis methodology to objectively quantify the performance of individual players in soccer through a complex pattern of interactions between teammates. McHale et al. (2012) developed a player performance index which is currently used within the top two tiers of English football. This system rates the performance of individual players on a quantitative scale, based on their contributions to weighted sub-indices. In basketball, the player efficiency rating is a broadly used objective rating system which measures a player's temporally-adjusted productivity based on positive and negative actions, and their outcomes (Travassos, Davids, Araújo, & Esteves, 2013). In ice hockey, Thomas, Ventura, Jensen and Ma (2013) developed a method to rate players based on both their offensive and defensive abilities. Their approach used a semi-Markov process to model scoring rates, whilst accounting for additional factors such as the quality of teammates and opponents, as well as the context of the game situation.

In addition to the notational literature, there has also been a variety of work developed in team sports with the emphasis on forecasting individual performance in an applied setting. One of the more renowned and commercially used systems is the 'Player Empirical and Optimisation

Test Algorithm' (PECOTA) model, which models the past performance statistics of comparable players to forecast a player's future performance in Major League Baseball (Silver, 2003). Unfortunately, little academic literature has been published on PECOTA, as it is predominantly used within the Major League Baseball's Prospectus (Silver, 2003). In addition to PECOTA, numerous other professional team sports have been successful in producing similar forecasting systems, including American football (Schatz, 2008), basketball (Pelton, 2008) and ice hockey (Awad, 2009).

2.7 Quantifying the individual in Australian Rules football

2.7.1 Scientific literature

There have been a number of studies which have used player performance data to quantify individual performances with respect to successful match outcome in AF. Heasman, Dawson, Berry and Stewart (2008) created a player impact rating by attributing numerical values to performance actions relative to their perceived worth. The rating values were weighted with respect to match situation, playing position, and were adjusted relative to a player's time on ground. Alternatively, Stewart et al. (2007) used various regression models to develop an 11-variable player ranking model, which quantifies player performance by valuing the most important performance actions with respect to Win/Loss margin. Both of these studies provide value for use in an applied setting by outlining methods to analyse and identify the impact and value in which individual players have on team performance. This provides value for sporting organisations by allowing an objective way to assess individual player performance with respect to other players, as well as relative to their own individual standard of performance;

thus having implications for both recruitment and benchmarking purposes, respectively (Heasman et al., 2008; Stewart et al., 2007). With the advances in player tracking technologies and increased collection of tactical performance indicators in AF over the past decade, various other ratings systems have been developed in AF allowing for a more detailed representation of the specific equity of particular actions. Each of these systems were developed and are maintained commercially, and have not been externally validated.

2.7.2 Commercially developed player ratings systems

There are a number of player ratings systems used for commercial purposes within the AFL. The three most prominent systems all use Champion Data as the source of match performance data. Two of these particular systems are used for the online fantasy competitions 'AFL Fantasy' and 'Supercoach', and utilise the most basic of Champion Data's quantifiable performance indicators within their player ratings systems (Borland, Lee & Macdonald, 2011; Herald Sun, 2016).

Specifically, the AFL Fantasy rating system awards each player rating points relative to the quantity of nine specific actions, each of which incur a fixed point allocation. This rather basic system is quite biased towards those whose roles allow for greater involvements, and disregards the difficulty and quality actions performed (Jackson, 2016b). Alternatively, the Supercoach competition uses the 'AFL Player Rankings' system, which takes a similar approach to that of the abovementioned method by Stewart et al. (2007). In this system, the AFL Player Rankings model is extended to include over 50 variables (Herald Sun, 2016). Similarly to the AFL fantasy rating system, the value of each action is fixed, however, the values used in this system were derived from a regression model to identify the importance of actions, using match score margin as the outcome variable (Jackson, 2016a). In addition, commonly performed actions are further classified. For example, rather than all kicks being deemed equal, there are six different types of kicks (long to advantage, long effective, short effective, backwards effective, ineffective and clanger), each acquiring different amount of points relative to their perceived difficulty (Herald Sun, 2016). To date there has been no external research to evaluate the validity of these two systems.

2.7.3 The official 'AFL Player Ratings'

The third commercially developed system, the 'AFL Player Ratings', is an objective system based on the principle of field equity, where a player's actions are quantified relative to how much their actions increase or decrease their team's expected value of the next score (Jackson, 2009). As such, a player's actions which improve the position of their team obtain a positive rating relative to the equity of the change. For example, if a player took possession of the ball in a contested situation close to their defensive goal, and was able to effectively dispose of the ball to a teammate in a less contested situation further away from their defensive goal, the value of the rating would likely be positive. Conversely, if a player's actions worsen the position of their team, this results in a negative rating relative to the difference in equity. An example of this would be if a player receives the ball under minimal pressure, and then disposes of the ball resulting in the opponent gaining possession. Each of the points acquired by a player's actions fall into one of 13 subcategories which describe the nature of the action. Figure 2.3 gives a visual representation of the subcategories, and how the AFL Player Ratings contributes points to each player's overall match rating. Due to its equity based nature and research-based design, the AFL Player Ratings system was the rating system used throughout the course of this thesis.

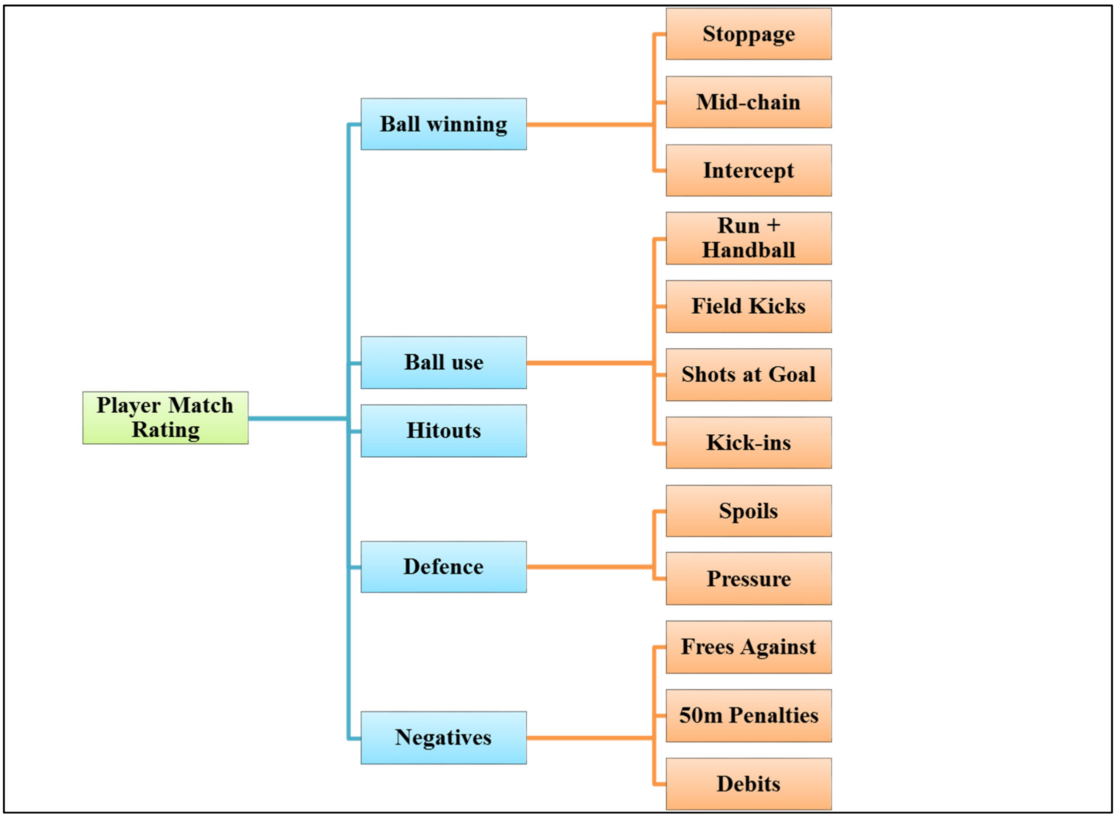

Figure 2.3 The categories and subcategories used to outline player match performance in the AFL Player Ratings.

2.8 Conclusion

Within the notational team sports literature there has been considerable research surrounding modelling player performance data for organisational decision support. Despite this, in comparison to various other invasion team sports played at a professional level, the volume of research conducted in AF is considerably behind. This void provides an opportunity to both develop new methodologies, and extend existing methodologies from other team sports to AF. With the large volume of player performance data, continual change in the gameplay and tactics, various rule changes and ongoing expansion of the elite Women's competition, various avenues for associated research to be applied at the elite levels of AF exist. Future work should focus on using the statistical models and machine learning methodologies outlined as part of this review to analyse player performance data to provide support for decisions faced by professional AF organisations.

CHAPTER THREE – STUDY I

Chapter Overview

Chapter Three is the first of four studies undertaken in this thesis. The study looks to assess the validity of the AFL Player Ratings metric, and serves to outline the suitability of the this metric for use as an objective measure of player performance prior to its use in the remaining studies of this thesis.

This chapter contains an abstract (section 3.1), introduction (section 3.2), methods (section 3.3), results (section 3.4), discussion (section 3.5) and conclusion (section 3.6) sections. The content of this chapter was published in the International Journal of Sports Science and Coaching (McIntosh, Kovalchik & Robertson, 2018b).

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1. PUBLICATION DETAILS (to be completed by the candidate)

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2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

Signature	Date
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3. CO-AUTHOR(S) DECLARATION

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3. There are no other authors of the publication according to these criteria;
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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
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Validation of the Australian Football League Player Ratings

3.1 Abstract

This study investigated the validity of the official Australian Football League Player Ratings system. It also aimed to determine the extent to which the distribution of points across the 13 rating subcategories could explain Australian Football League match outcome. Ratings were obtained for each player from Australian Football League matches played during the 2013-2016 seasons, along with the corresponding match outcome (Win/Loss and score margin). The values for each of the 13 subcategories that comprise the ratings were also obtained for the 2016 season. Total team rating scores were derived as an objective team outcome for each match. Percentage agreement and Pearson correlational analyses revealed that winning teams displayed a higher total team rating in 94.2% of matches and an association of r = 0.96 (95% confidence interval = 0.95-0.96) between match score margin and total team rating differential, respectively. A Partial Decision Tree (PART) analysis resulted in seven rules capable of determining the extent to which relative contributions of rating subcategories explain Win/Loss at an accuracy of 79.3%. These models support the validity of the Australian Football League Player Ratings system and its use as a pertinent system for objective player analyses in the Australian Football League.

3.2 Introduction

Performance analysis is used within sporting organisations to support decision-making processes relating to an individual or team's performance (Hughes & Bartlett, 2002; Travassos et al., 2013). In many professional sports, various rating systems have been proposed with the aim of encapsulating player or team performance on a quantitative scale (McHale et al., 2012; Radovanović et al., 2013; Stefani & Pollard, 2007; Szczepański, 2008). In individual sports, the match result can be used as an objective outcome to directly compare against performance (McHale et al., 2012). Similarly, in team sports such as baseball, individual performance has been objectively quantified as a result of direct player actions (Chao-Chien, 2014; Streib et al., 2012). However, rating individuals within invasion team sports such as Australian Rules football (AF) and football is more complex (Gerrard, 2007). This is in part due to the absence of objectively quantifiable outcomes that emanate directly from player actions, but also the dynamic nature, varied individual roles and complex interactions which exist between individuals in these sports (Robertson, Back, et al., 2015; Travassos et al., 2013).

Within the elite competitions of many invasion team-based sports, an increase in the collection and reporting of performance data has led to the existence of more detailed and comprehensive performance rating systems (Hutchins, 2016). This has in turn resulted in those responsible for making organisational decisions become more reliant on performance data to make inferences about player performance and support their decision-making processes (Hutchins, 2016). McHale et al. (2012) developed a player performance index which is used within the top two tiers of English football. This system rates the performance of individual players on a quantitative scale, based on their contributions to weighted subindices. Similarly in basketball, the player efficiency rating is a broadly used objective rating system which measures a player's temporally adjusted productivity based on positive and negative actions and their outcomes (Radovanović et al., 2013).

Australian Rules football is an invasion team sport played on an oval field between two opposing teams consisting of 22 players each (18 on the field and 4 interchange). The ball is moved about the field by kicking, handballing or running with the ball, with scoring achieved by kicking the ball between large goal posts located at either end of the field. Within the elite competition of AF, the Australian Football League (AFL), various subjective rating systems have been proposed that quantify an individual's match performance. However, these are susceptible to biases, such as personal views and emotional reflection, which are known to accompany such subjective analyses (Ayres, 2008; Norman, 1993). For instance, the AFL Coaches Association awards a champion player each year. Votes for this are cast following each match by the senior coaches from both competing teams on the most influential players from their respective match.

From an objective perspective, Heasman et al. (2008) created a player impact rating by attributing numerical values to performance actions relative to their perceived worth, weighting these values according to match situation and then adjusting relative to a players time on ground. Following the release of the novel *Moneyball* (Lewis, 2004), Stewart et al. (2007) determined whether similar statistical methods could be applied to the AFL. Using data from five seasons, they created an 11-variable player ranking model by identifying the most important performance actions and then including those with the strongest statistical relationship to team winning margin. The 'AFL Player Rankings', which is produced by statistics provider Champion Data Pty Ltd and is the system used by the fantasy competition *SuperCoach* (www.supercoach.heraldsun.com.au), takes a similar approach to that of Stewart et al. (2007) however extends their model to include over 100 variables (Herald Sun, 2016). To date, there has been no external research to evaluate the validity of these systems.

Recently, a new alternative to the abovementioned systems has been proposed; the 'AFL Player Ratings' (http://www.afl.com.au/stats/player-ratings/ratings-hub). Produced by Champion

Data, it is an objective system based on the principle of field equity, where a player's actions are quantified relative to how much their actions increase or decrease their team's expected value of the next score (Jackson, 2009). For example, when a player obtains the ball in a contested situation a long distance away from (Ballı & Korukoğlu, 2014) their attacking goal, the expected value of next score is likely to be low (or negative, meaning in the given situation, the opposition is more likely to score). Conversely, if a player receives the ball uncontested, with minimal pressure and is close to their own goal, the expected value of the next score will be high. This expected value is based on contextual information relating to each possession (i.e., pressure from opponents, field position, time of the match) and is determined by the outcomes from every possession collected from all AFL matches preceding back to the 2004 season (Jackson, 2009). Furthermore, the rating points awarded to (or taken from) a player for each action falls into to one or more categories which describe the nature of the action. These categories are defined in Table 3.1. The primary aim of this study was to determine the construct validity of the AFL Player Ratings system, using data collected from the 2013–2016 AFL seasons. The secondary aim was to determine the extent to which the distribution of points recorded by teams across the 13 rating subcategories could be used to explain AFL match outcome. This study incorporated two phases; the first phase focuses on the derived total team ratings, whilst the second phase considers the 13 player rating subcategories.

Table 3.1 Definitions of the 13 AFL Player Ratings subcategories used in this study.

Category	Subcategory	Description
Ball Winning	Stoppage	Points from possessions won pre-clearance at stoppages.
	Mid Chain	Points from possessions excluding those won at stoppages or as intercepts.
	Intercepts	Points from intercept possessions.
Ball Use	Run and Handball	Points from handballs, and ball carrying between the possession and handball.
	Field Kicks	Points from field kicks.
	Shots at Goal	Points from shots at goal.
	Kick-ins	Points from kick-ins.
Hitouts	Hitouts	Points from hitouts to advantage and points lost from hitouts to opposition. Neutral hitouts gain zero points.
Defence	Spoils	Points from spoils.
	Pressure	Points from pressure - including tackles and smothers.
Negatives	Frees Against	Points lost from frees against.
	50 metre Penalties	Points lost from 50 metre penalties against.
	Debits	Points lost from dropped marks, no pressure errors and missed tackles.

3.3 Methods

3.3.1 Phase one: Construct validity of the AFL Player Ratings system

Individual ratings data were obtained from Champion Data Pty Ltd, for all 827 matches played throughout the 2013–2016 AFL seasons. This included 22 matches from each team during the regular season rounds, as well as 9 matches played throughout the finals series each season. One match was abandoned prior to play during the 2015 season. Match result was obtained for each match and expressed as (a) *outcome* (Win/Loss) and (b) *margin* (points score differential). Prior to data *c*ollection, the study was approved by the relevant human research ethics committee.

Total team ratings were derived for each match by accumulating the 22 individual player ratings from the same match. The total team rating was derived with the aim of providing an objective independent variable to be modelled against outcome and margin. This was completed for each of the AFL teams (n = 18), for each match played throughout the four seasons. Prior to statistical analysis, the four drawn matches that occurred throughout the 2013–2016 seasons were removed from the analyses.

For the remaining 823 matches, a percentage agreement analysis was used to construct a model explaining outcome as a function of higher total team ratings. Descriptive statistics (mean ± standard deviation) of the total team ratings were also collected across the four seasons to gauge the *c*onsistency of the system across seasons. In order to gauge the strength of total team rating differential as a continuous variable, a Pearson's correlation analysis was employed to determine the extent of its relationship with margin. This analysis was undertaken using the *Hmisc* package (Harrell Jr, 2017) in the R statistical computing software version 3.3.2 (R Core Team, 2016). Correlations were obtained considering the entire dataset, as well as separately within team and across the whole competition for individual seasons, allowing for assessment of both inter-team and inter-season variations, respectively.

3.3.2 Phase two: Relationships between the distribution of AFL Player Ratings subcategories and match result

To address the secondary aim, data from each subcategory of each individual's player ratings were obtained from Champion Data Pty Ltd. These analyses were limited to the 207 matches played throughout the 2016 AFL season due to data availability.

Descriptive statistics (mean ± standard deviation) for all 13 subcategories were obtained across the season. In order to determine the relationship of each subcategory with match result, the total team ratings (as calculated in phase one) were broken down into separate contributions from each subcategory for each match. In order to allow for repeat observations across all teams and each round throughout the season, the data were then descriptively converted from its absolute format into a relative format (Ofoghi, Zeleznikow, MacMahon & Raab, 2013). For example, if a team's match rating was 250 points, of which 30 points were attributed by the subcategory field kicks, then the team's relative contribution of field kicks for this particular match would be analysed as 12%.

To determine the extent to which the separate contributions from each subcategory related to outcome, a rule induction analysis was undertaken using the *RWeka* package (Hornik, Buchta & Zeileis, 2009). A PART algorithm (Frank & Witten, 1998) was used to generate a list of rules capable of explaining outcome. For this analysis, overall classification accuracy (%) and 10-fold cross-validation accuracy were used as the two model performance measures. A number of parameters were trialled in the model development, with best performance based on the abovementioned measures obtained using a minimum of 20 instances in order for a node to split and minimum confidence set to 0.5.

3.4 Results

3.4.1 Phase one: Construct validity of the AFL Player Ratings system

Results from the percentage agreement analysis found that winning teams had a higher total team rating in 94.2% of matches (775 of 823 instances), with winning teams averaging 232.1 ± 27.2 rating points across the four seasons and losing teams averaging 192.1 ± 25.5. The density of total team ratings difference for winning teams is outlined in Figure 3.1, and the distribution of total team ratings for winning and losing teams across the four seasons is shown in Figure 3.2.

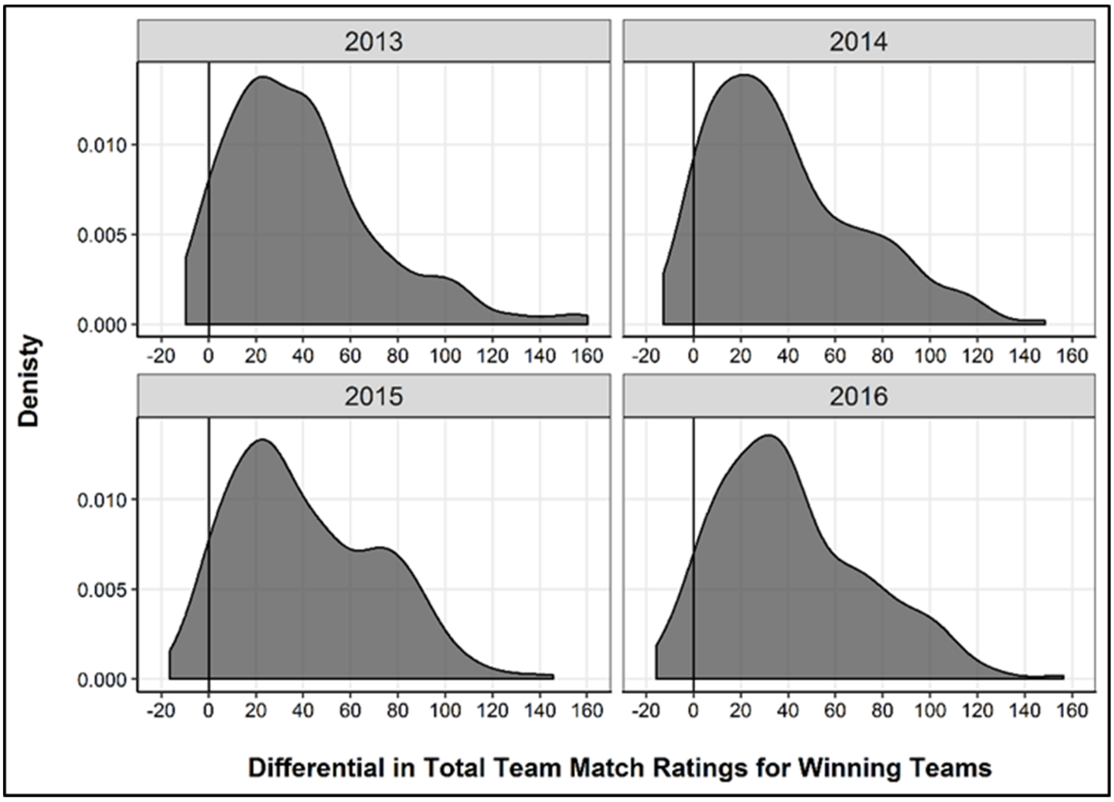

Figure 3.1 Density plot displaying the distribution of differentials in total team ratings for winning teams across the 2013-2016 seasons.

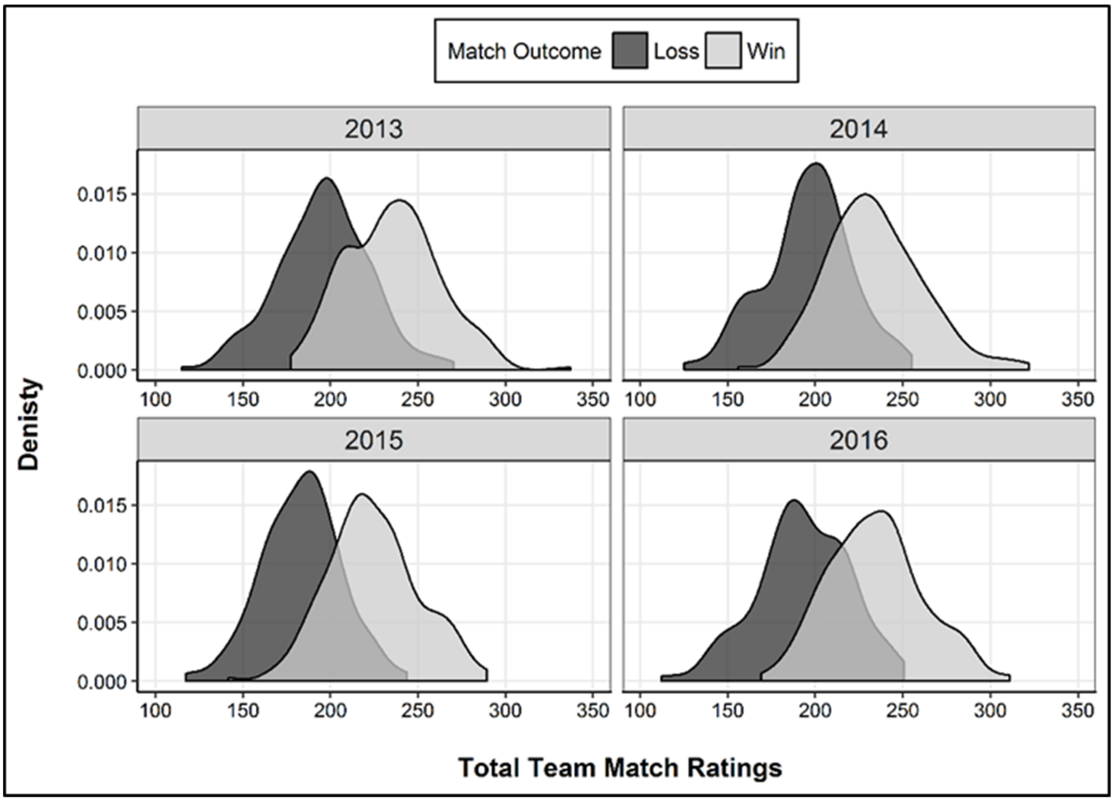

Figure 3.2 Density plot displaying the distribution of total team ratings across the 2013-2016 seasons.

The Pearson's correlation analysis indicated a strong association (r = 0.96, 95% confidence interval (CI) = 0.95–0.96) across the 18 teams in the competition, between margin and total team rating. The association for each of the 18 teams varied from r = 0.92 to r = 0.97 (95% CI = 0.89–0.96 and 0.95–0.98, respectively), and across the four seasons from r = 0.95 to r = 0.96 (95% CI = 0.94–0.95 and 0.96–0.97, respectively). The scatterplot shown in Figure 3.3 displays the linear association between margin and total team rating, indicating a homoscedastic distribution.

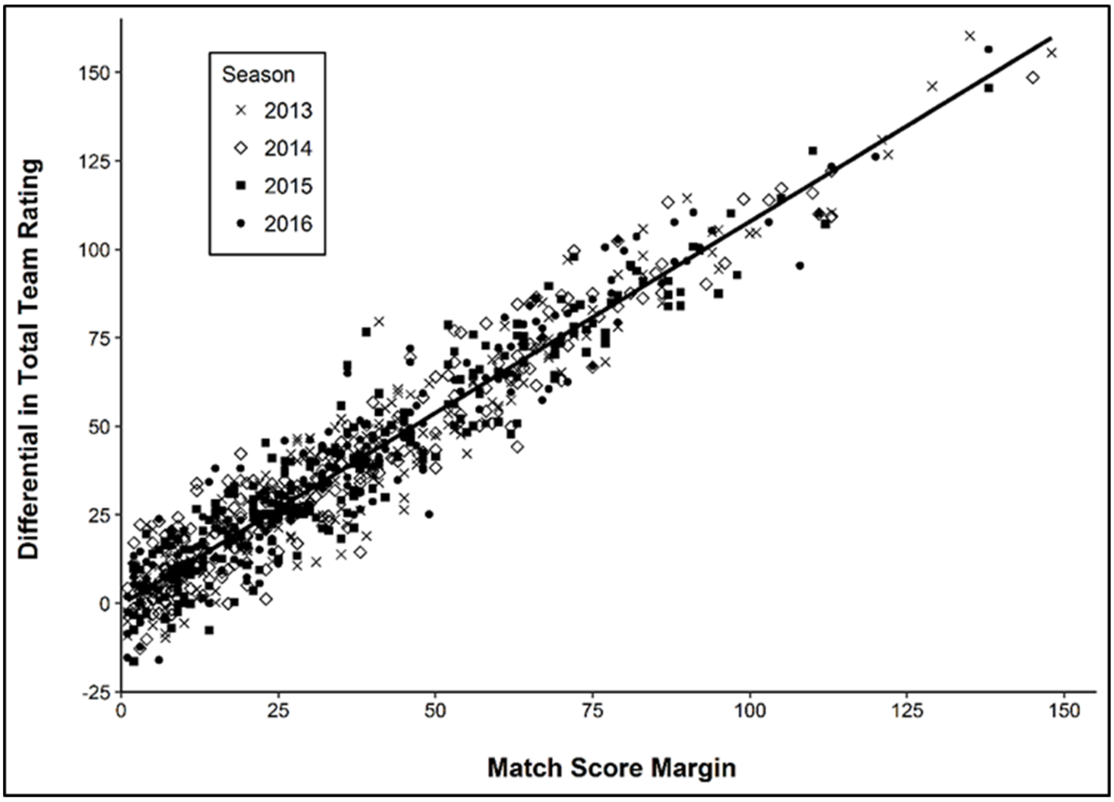

Figure 3.3 Scatterplot displaying the homoscedasticity of the distribution between margin and total team rating differentials across the 2013-2016 seasons.

3.4.2 Phase two: Relationships between the distribution of AFL Player Ratings subcategories and match result

Descriptive statistics relating to each of the subcategories and how their contributions differentiate between wins and losses are outlined in Figure 3.4. Results show that on average, winning teams had a higher contribution of team rating points in only the four subcategories which relate to ball use (run and handball, field kicks, shots at goal and kick-ins). The final PART model revealed seven rules explaining outcome at an accuracy of 79.3% (314 of 396 matches). The class accuracy rates in the data for each outcome were 70.2% for wins and 88.4% for losses. Results from the cross-validation revealed a decrease in classification accuracy of 6.1%, with an overall classification of 73.2% retained. The seven rules included in the model are presented in Table 3.2. The percentage values represent the contribution from each subcategory to team total rating.

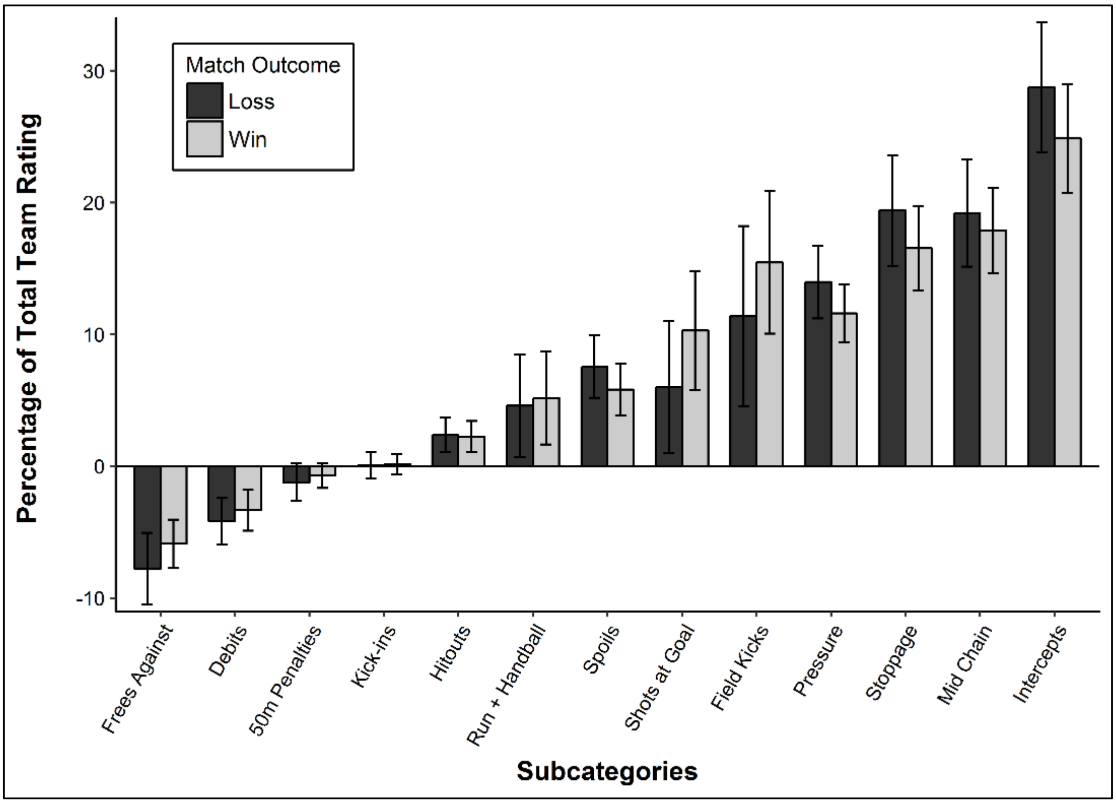

Figure 3.4 **Histogram displaying the descriptive statistics (mean ± standard deviation) of the relative contribution to team total rating from each of the subcategories across the 2016 season.**

Table 3.2 PART model explaining outcome from the relative contributions of each subcategory to team total rating.

Rule		Outcome	Correctly classified	Incorrectly classified
Rule 1	Intercepts > 27.1% AND Frees Against > -9.6% AND Shots at Goal > 4.2% AND Pressure > 11.6%	Loss	60	19
Rule 2	Shots at Goal ≤ 4.3%	Loss	87	14
Rule 3	Frees Against > -9.4% AND Spoils ≤ 4.9% AND Shots at Goal > 10.8%	Win	62	10
Rule 4	Spoils ≤ 4.9%	Win	62	4
Rule 5	Field Kicks < 15.2%	Loss	39	17
Rule 6	Pressure > 12.9%	Loss	48	9
Rule 7	Else	Win	38	9

3.5 Discussion

The primary aim of this study was to determine the construct validity of the AFL Player Ratings system. Phase one focused specifically on the ability of the AFL Player Ratings system to relate to match result when expressed in both a binomial (outcome) and continuous manner (margin). The findings revealed that the AFL Player Ratings system is strongly associated with match result irrespective of how it is expressed, suggesting that the system has good validity for assessing combined player performance in AF. The findings of the correlational analysis support the findings of the percentage agreement, highlighting that in the very low proportion of matches where agreement was not reached, both the margin and team total rating differential were both very small. The strength of these associations emphasise how incorporating considerations about the equity of a player's actions is a viable method of quantifying aggregated player performance.

Phase two focused on determining the extent to which the distribution of points across the 13 rating subcategories could be used to explain outcome. Descriptive statistics revealed that only those subcategories relating to ball use had a higher average contribution to team rating points by winning sides. This is likely a result of the ball use subcategories being the only four subcategories in which rating points can be both awarded and deducted. Therefore, contributions of points within these subcategories are further impacted by whether actions increase or decrease their team's expected value of the next score. Of the 13 subcategories included in the analysis, 6 are outlined in the PART model. Specifically, the model indicates a positive relationship between larger contributions of shots at goal and field kicks with successful outcome. This is unsurprising due to the function of scoring on match result, and the known relationship between maintaining ball possession and match result in AF (O'Shaughnessy, 2006), respectively. Additionally, the positive relationship seen in these two subcategories is again likely associated with the ability to both gain and lose rating points in these subcategories. Conversely, the model indicates an inverse relationship between larger contributions of pressure, spoils and intercepts with match outcome. Although points are awarded to players for actions in these subcategories, having above-average relative contributions in these subcategories reflects lower contributions in other subcategories, specifically those relating to ball use.

The absence of the remaining seven subcategories from the model is likely to be multifaceted. Specifically, for run and handball, kick-ins, hitouts, 50 metre penalties and debits, a comparatively low overall contribution to team total ratings as well as small variation in mean values between wins and losses may have contributed to their absence. For stoppages and mid chain, despite a relatively higher overall contribution to team total ratings, their absence is potentially due to small variations to mean values between wins and losses.

As this study takes a specific focus on objective performance, an assumption was made that the sum of a team's parts (individual contributions) combine to create the result, therefore utilising successful team performance as an objective dependent variable. As such, this study focused on how the AFL Player Ratings reflect team results to provide a validation of the metrics construct. Heasman et al. (2008) took a similar approach in the validation of their player impact model, finding their team impact scores were higher in winning teams in 86.4% of matches (19 of 22 instances), and had a strong correlation with margin (r = 0.85). In comparison, the findings of both the percentage agreement and Pearson's correlation models in this study had stronger relationships with respect to match outcome and margin, respectively. A larger sample size was also used. Stewart et al. (2007) also considered score margin to identify which player statistics are most important in terms of their contribution to match outcome. Their findings indicate that kicks travelling more than 40 metre and kicks that go directly to an opposition player have large positive and negative coefficients, respectively. Thus reiterating the findings of phase two in this study, indicating that actions relating to ball use have the largest impact on match outcome. It is not known as to whether the AFL Player Ratings displays higher construct validity comparative to popular fantasy football metrics; however, future research may look to determine this. Though adopting a team approach for this validation was necessary, future research should look to assess the contribution of individual player ratings on team performance. Specifically, it may be of interest to consider whether the distribution of performances across the 22 players in each team has an effect on team performance.

In team sports, the analysis of objective performance data relating to discrete player actions (i.e., kicks/handballs, whilst factoring in contextual information such as pressure from opponents, field position, time of the match, etc.) can be a viable strategic resource. Specifically within AFL teams, objective rating systems can be used for various aspects of organisational decision support. For example, each AFL club has approximately 45 players on their roster (maximum 47) and is constrained in their ability to recruit players by a salary cap. Furthermore, only 22 of these players are selected to play each round. This in turn puts a greater emphasis on decisions made with respect to player contracting and the development of players within their roster, as well as weekly player selection, respectively. Applications of the AFL Player Ratings could be made in order to gain a greater understanding of what makes an individual player unique, what areas they lack in and also to forecast the level of performance expected from players in the future.

Despite the strength of the PART model produced in phase two of this study, its generalisability is unknown, as it was limited to the 2016 AFL season due to the data availability. In order to test the generalisability of this model, an external validation should be undertaken when data become available for subsequent AFL seasons, to assess whether longitudinal variations exist.

3.6 Conclusion

The results from this study support the validity of the AFL Player Ratings system and its ability to objectively assess combined player performance in AF. By utilising objective outcomes as dependent variables, a more thorough understanding of how equity is used as a quantifiable measure to relate to successful performance can be achieved. To further refine the generalisability of the model produced in phase two, subsequent seasons of data could be added once they become available. Future work should focus on the continual development of improving the ratings system as new technologies become available, as well as the interpretation and application of the AFL Player Ratings system for objective performance analysis and operational decision-making.

CHAPTER FOUR – STUDY II

Chapter Overview

Chapter Four is the second of the studies contained in this thesis. The study looked to identify whether the performance profiles created from the proportion of rating points in each AFL Player Rating subcategory could be used to classify players into *a priori* determined player role categories. Additionally, it looked to determine the level of similarity between the playing styles of each individual player competing within the AFL. An application was developed from the two models in this study to visually represent the similarity of players within the squad of a single AFL club.

This chapter contains an abstract (section 4.1), introduction (section 4.2), methods (section 4.3), results (section 4.4), discussion (section 4.5) and conclusion (section 4.6) sections. The content of this chapter was published in the International Journal of Performance Analysis in Sport (McIntosh, Kovalchik & Robertson, 2018a).

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1. PUBLICATION DETAILS (to be completed by the candidate)

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2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

Sam McIntosh Digitally signed by Sam McIntosh DN: cn=Sam McIntosh, o, ou, email=sam.mcintosh@live.vu.edu.au, c=AU Date: 2019.08.20 06:59:21 +10'00'	20/08/2019
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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Stephanie Kovalchik	5	Assisted with methodology design. Feedback and revisions for methodology.	Stephanie Kovalchik Digitally signed by Stephanie Kovalchik Date: 2019.08.21 15:45:07 +10'00'	21/8/19
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.	Sam Robertson Digitally signed by Sam Robertson Date: 2019.08.19 20:35:32 +10'00'	19/8/19

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Examination of player role in the Australian Football League using match performance data

4.1 Abstract

This study developed multiple methods to determine player role in Australian Rules football utilising objective match performance data. Specifically, Australian Football League (AFL) Player Ratings from the 2016 AFL season were used to classify players into seven *a priori* determined playing roles, as well as determine levels of individual player similarity. Mean values for the 11 AFL Player Ratings categories were calculated for each individual player, and a performance profile created based on the relative contribution of points from each category to that players overall rating total. A decision tree model incorporated five of the 11 categories to classify player role at an accuracy of 74.3% (95% confidence interval = 70.5-77.9% across 10-fold cross-validation). Role classification was most accurate for key forwards, midfielders and general defenders, whilst the midfield-forward role was most difficult to define objectively. A Euclidean distance measure was used to determine the most similar pairs of individual players within the AFL, as well as from an intra-club perspective. An application was also developed to visually represent the similarity of players within the squad of a single AFL club. Sporting organisations may apply the methods provided here to support decisions regarding player selection and recruitment.

4.2 Introduction

Professional sporting organisations utilise objective performance data to assist with decision support processes (Kuper, 2012; Wright et al., 2013). The use of objective data for such purposes can help to improve performance outcomes and reduce the financial costs of identifying individuals who possess attributes of perceived relevance (Ofoghi, Zeleznikow, MacMahon & Raab, 2013; Pion et al., 2016).

Within team sports, organisations regularly face decisions regarding player identification and selection. At a macro level this relates to player recruitment, such as which players to draft, the length of contracts offered and the level of financial remuneration offered in order to meet any total player payment restrictions (i.e., league salary cap). On a micro level, such decisions relate to weekly player selection, including identifying optimal team line-ups and replacing injured players. Each of these decisions typically involves a level of consideration about the specific attributes in which each player can bring to the team/club list (Tavana et al., 2013; Trninić et al., 2008). Through the analysis of objective player performance data, objective models can be created to support these decision-making processes (Ofoghi, Zeleznikow, MacMahon & Raab, 2013).

Examples of decision support applications in sport include Boon and Sierksma (2003), who developed a linear optimisation model to determine player line-ups in volleyball, including both starting and rally positions relative to the individuals on the court. Maymin (2017) developed a random forest projection model that outperformed human decisions relating to the draft, free agency and trades, in the National Basketball Association. Pion et al. (2016) developed models to reduce the risk of overlooking high-potential gymnasts based on findings from a multidimensional talent identification assessment. In the Australian Rules football (AF) notational literature, Robertson, Woods, et al. (2015) used a rule induction algorithm to explain player selection level (i.e., drafted and non-drafted), relative to their physical performance and anthropometric attributes. Similarly, Woods et al. (2015) used a multivariate analysis of variance and logistic regression to determine the relationships between playing status (i.e., elite and sub-elite) and physical/anthropometric parameters.

The Australian Football League (AFL) is the elite competition of AF. Comparative to many other team sports, play is less structured, with players not constrained by an offside rule (i.e., football and rugby), nor to certain field zones (i.e., netball). This allows players to potentially perform a variety of roles across the entire field of play. Despite this, individuals are still typically classified by their playing position (Ractliffe, 2017). For example, Dawson, Hopkinson, Appleby, Stewart and Roberts (2004) determined differences in movement patterns across playing positions. Similarly, Stares, Dawson, Heasman and Rogalski (2015), utilised playing position to identify the specific differences in physical demands of a match.

There has also been research in AF investigating player role and similarity. Alternatively to this study, the majority of this research has typically used physical characteristics and technical skill indicators to determine playing role. Examples include, Barake, Mitchell, Stavros and Stewart (2016) who used a multinomial logistic regression to classify players based on their ground location, anthropometric characteristics and performance indicators, such as possessions, tackles and spoils. Sargent and Bedford (2010) grouped players into positional categories based on Mahalanobis distances from positional centroids using 13 game related performance variables. In elite junior AF, Woods, Veale, et al. (2018) used a linear discriminant analysis, a random forest, and a PART decision list to determine whether technical skill indicators categorised a player's role. Jackson (2016b) used vector angles to determine the similarity between individual players based on contextual performance data relating to each player's most common match involvements.

Inferences can be made about a player's performance and value by assessing the outcomes which result from their actions. Although differing individuals may be categorised as playing the same position, they may nonetheless offer different qualities to their team. Specifically, a defender may be desirable for recruitment or selection by some teams because they rarely allow their direct opponent to score. However, the same player's ability to distribute the ball effectively or accelerate and carry the ball out of defensive areas may also be valued. In this study, the player role classifications used by Champion Data (Champion Data Pty Ltd., Melbourne, Australia) are considered. These role classifications are determined based on the relative amount of time a player spends in certain regions of the ground (Jackson, 2016b), and are used to determine whether profiles created by a players actions can accurately describe player role.

The AFL Player Ratings were designed in order for the value of individual player actions to be objectively measured based on the principle of field equity. In this metric, points are awarded to (or deducted from) a player relative to how much their actions increase or decrease their team's expected value of the next score, based on contextual information relating to each possession (Jackson, 2009; McIntosh et al., 2018b). For example, when a player obtains the ball in an uncontested situation close to their attacking goal, the expected value of next score is likely to be high. Alternatively, when a player receives the ball under pressure and is close to their opponent's goal, the expected value of the next score will be low. Each of these actions fall into to one or more of the 11 AFL Player Ratings categories, which describe the nature of the action. In this study, player performance profiles were developed based on the proportion of rating points in each of these AFL Player Rating categories. Such profiles have been created using comprehensive in-game skill indicator sets in the wider team sport literature (James, Mellalieu & Jones, 2005; Liu, Gómez, Gonçalves & Sampaio, 2016; O'Donoghue, Mayes, Edwards & Garland, 2008).

This study aimed to identify whether the abovementioned performance profiles could classify players into *a priori* determined player role categories (classified by Champion Data). Secondly, the profiles were then utilised to create a dissimilarity matrix to identity the closeness of playing styles between each individual player within the AFL.

4.3 Methods

4.3.1 Data

AFL Player Ratings data were acquired from Champion Data, for all 207 games played during the 2016 AFL season. The totals for each of the 11 categories that comprise a player's match rating were collected and compiled. These categories are defined in Table 4.1. A profile for each player (n = 656) was compiled by obtaining their average rating points from each category across the full season. The relative (percentage) amount of points each category contributed to that player's total of rating averages was then calculated. Table 4.2 outlines two of these created player profiles; the examples chosen outline how two players with similar average rating scores can have considerably different contributions from the 11 different categories. Additionally, classifications of player role were collected for each player, based on Champions Data's final assessment at the end of the 2016 AFL season. These player role classifications are defined in Table 4.3. Players were required to play a minimum of four matches to be included in the analyses, reducing the sample to $n = 560$. This was done to ensure there was sufficient data to give a representative summary of their typical performance.

Table 4.1 Champion data definitions of the 11 AFL Player Rating categories.

Category Type	Category	Description
Ball Winning	Stoppage	Points from possessions won pre-clearance at stoppages.
	Mid Chain	Points from possessions excluding those won at stoppages or as intercepts.
	Intercepts	Points from intercept possessions.
Ball Use	Run and Handball	Points from handballs, and ball carrying between the possession and handball.
	Field Kicks	Points from field kicks.
	Shots at Goal	Points from shots at goal.
	Kick Ins	Points from kick ins.
Hitouts	Hitouts	Points from hitouts to advantage and points lost from hitouts to opposition. Neutral hitouts gain zero points.
Defence	Spoils	Points from spoils.
	Pressure	Points from pressure - including tackles and smothers.
Negatives	Negatives	Points lost from frees against, 50 metre penalties against, dropped marks, no pressure errors and missed tackles.

Table 4.2 **Example profiles of two players (Alex Rance and Bryce Gibbs) with similar average rating scores, but substantially different relative breakdowns.**

	Stoppages	Mid Chain	Intercepts	Run and Handball	Field Kicks	Shots at Goal	Kick Ins	Hitout	Spoils	Pressure	Negatives	Total
Alex Rance												
Average rating points	0.12	0.31	8.34	1.00	0.79	0.00	0.07	0.00	3.95	0.63	-2.06	13.17
Relative rating points	0.01	0.02	0.63	0.08	0.06	0.00	0.01	0.00	0.30	0.05	-0.16	1.00
Bryce Gibbs												
Average rating points	4.08	1.28	1.62	0.90	2.02	1.75	0.00	0.65	0.09	1.97	-1.23	13.14
Relative rating points	0.31	0.09	0.12	0.07	0.15	0.13	0.00	0.05	0.01	0.15	-0.09	1.00
Relative difference	**-0.30**	**-0.07**	**+0.51**	**+0.01**	**-0.09**	**-0.13**	**+0.01**	**-0.05**	**+0.29**	**-0.10**	**-0.07**	

Table 4.3 Descriptions of the seven player roles used in this study.

Player Roles	Description
General Defender	Plays a role on opposition small-medium forwards and usually helps create play from the backline
Key Defender	Plays on opposition key forwards with the primary role of nullifying his opponent
General Forward	Plays predominantly in the forward half of the ground but with more freedom than a key forward
Key Forward	Plays predominantly as a tall marking target in the forward line
Midfielder	Spends the majority of time playing on the ball or on the wing
Midfield-Forward	Splits time equally between the forward line and the midfield. Often lines up on the half-forward flank but plays a significant amount of time in the midfield
Ruck	Has the primary role of competing for hit-outs at a stoppage

4.3.2 Statistical analysis

Descriptive statistics (mean and standard deviation) of the AFL Player Rating categories were calculated for each of the *a priori* defined player role classifications (n = 7). These indicators were then visualised using a basic bar plot to show the distribution of the data. A recursive partitioning and regression tree model (Breiman et al., 1984) was used to classify players into their *a priori* determined player role classifications based on the relative contributions outlined in their performance profiles. This analysis was undertaken using the *rpart* package (Therneau, Atkinson & Ripley, 2015) in the R statistical computing software version 3.3.2 (R Core Team, 2016). A required minimum of 75 cases were needed for a node to split, and the complexity parameter was set at 0.005 in order to include all player roles in the model. These measures were undertaken in order to avoid overfitting and to produce a more parsimonious model. Results of the model were averaged across 10-fold cross-validation and displayed using a tree visualisation and a confusion matrix.

The performance profile of each player was then analysed using Euclidian distances to model the level of dissimilarity between individual players. This analysis was undertaken using the *stats* package (R Core Team, 2016). The Euclidian distances were outputted as a matrix providing a measure of the dissimilarity between each individual player. Results of the model were expressed as the dissimilarity measures for the five most similar pairs of individuals from within the whole AFL, as well as those most similar to a specific player. A secondary matrix was created using only the players from one AFL club list. A network plot was created from this secondary matrix to create a practical decision support application, whereby each player is connected to their three most similar players at a length relative to each pairs level of similarity. Additionally, each player's role classification, as determined by the classification tree model, and average absolute AFL Player Rating over the 2016 season is highlighted.

4.4 Results

Descriptive statistics for each of the *a priori* player role classifications are presented in Figure 4.1. The overall classification accuracy of the model was reported at 74.3% (95% confidence interval = 70.5–77.9) for the 10-fold cross-validation. The final model is presented in Figure 4.2 and shows that intercepts, spoils, mid chain, hitouts and stoppages all contributed to the model; with the fractions indicating the absolute classification rate at the node (i.e., in actual numbers of players). A confusion matrix outlining the absolute true and false positive classifications, as well as the overall classification rate for each player role is outlined in Table 4.4.

Figure 4.3 displays how the nodes from the tree output can be visualised. The relative contributions to three of the four categories from the right-hand branch of the classification tree are plotted with respect to a player's *a priori* player role classification. The x- and y-axis intercept lines represent the levels at which nodes one and three split from the classification tree model (intercepts and mid chain, respectively). With respect to the other player roles, both key and general defenders acquire a considerable proportion of their rating points from intercepts (averaging 47.1% and 54.5% of rating points, respectively, compared to 13.6–21.7% for all others). Similar patterns are seen for both key and general forwards with rating points from mid chain (49.1% and 32.2%, respectively, compared to 4.2–21.2% for all others), and for midfielders, rucks and midfield-forwards with respect to rating points from stoppages (30.3%, 27.8 and 24.9%, respectively, compared to 2.7–10.8% for all others).

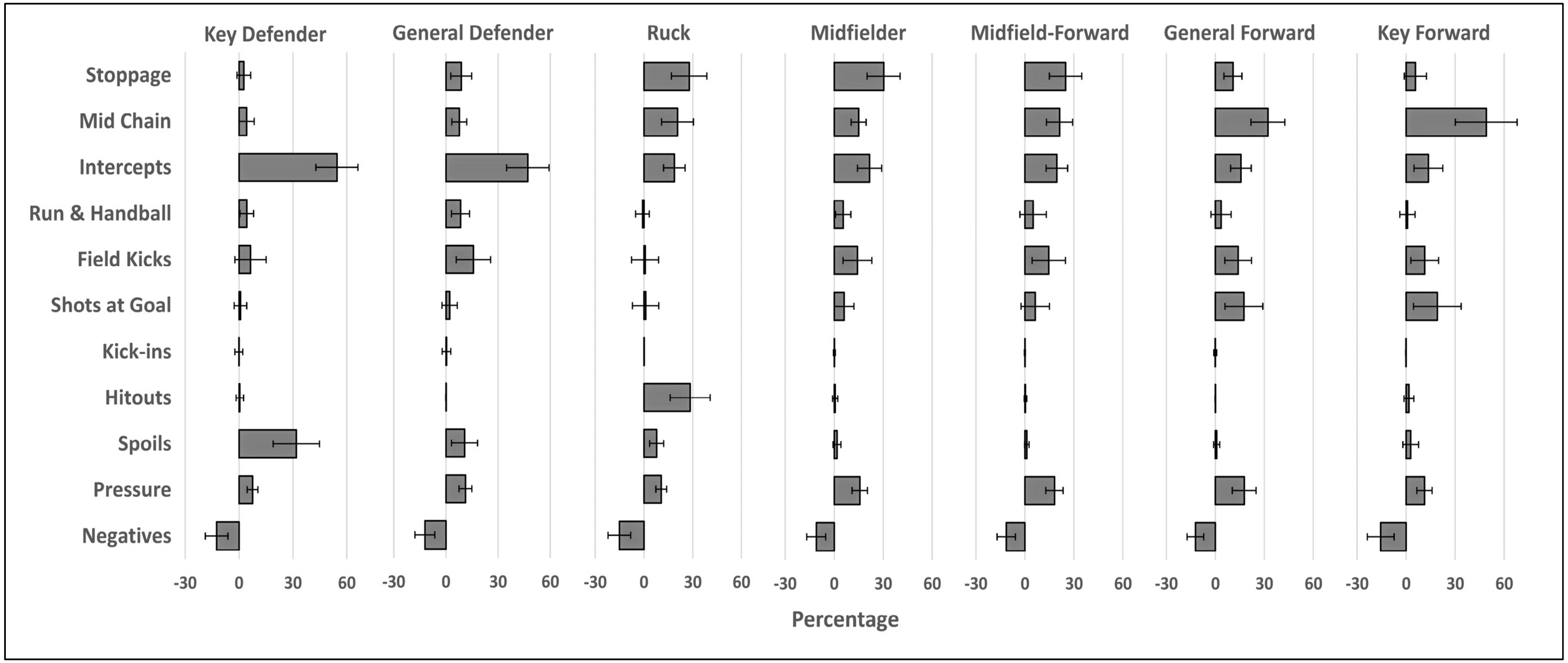

Figure 4.1 **Descriptive statistics (mean ± standard deviation) of the relative contributions from each of the AFL Player Rating categories, by each player role classification across the 2016 season.**

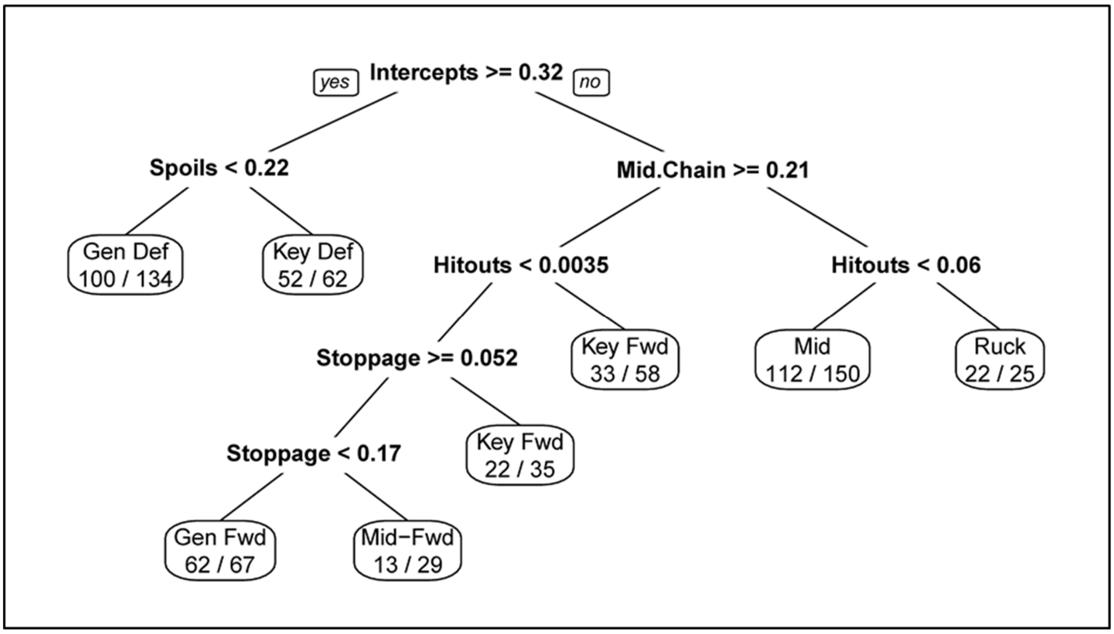

Figure 4.2 Classification tree model explaining player role classification rates for the 560 players who played four or more games during the 2016 AFL season. Fractions indicate the absolute classification rate at the node. "Gen Def", General Defender; "Gen Fwd", General Forward; "Key Def", Key Defender; Key Fwd", Key Forward; "Mid", Midfielder; "Mid-Fwd", Midfield-Forward.

Table 4.4 Confusion matrix for the classification tree model.

	Gen Def	Gen Fwd	Key Def	Key Fwd	Mid	Mid-Fwd	Ruck	Total (560)	Classification rate
Gen Def	100	0	10	0	11	1	0	122	0.820
Gen Fwd	1	62	0	15	6	10	0	94	0.660
Key Def	16	0	52	0	0	0	1	69	0.754
Key Fwd	2	1	0	55	0	0	0	58	0.948
Mid	11	0	0	4	112	5	2	134	0.836
Mid-Fwd	2	4	0	8	21	13	0	48	0.271
Ruck	2	0	0	11	0	0	22	35	0.629

"Gen Def", General Defender; "Gen Fwd", General Forward; "Key Def", Key Defender; "Key Fwd", Key Forward; "Mid", Midfielder; "Mid-Fwd", Midfield-Forward.

From the dissimilarity matrix, those individual player's with the most similar playing roles can be identified. Table 4.5 outlines the top five most similar player combinations and their level of dissimilarity. Table 4.6 highlights the players most similar to a specific player and their level of dissimilarity.

By filtering the players included in the model, the dissimilarity within specific groups can be highlighted. For example, Figure 4.4 outlines the level of dissimilarity through a network plot visualisation of one AFL club list. This figure shows that the three key forwards, along with two general forwards form a separate network to the remainder of the squad. Additionally, the general defenders form a link between the key defenders and the midfielders, whilst the remaining general forwards, and the only ruckman and midfield-forward, form links with the network of midfielders.

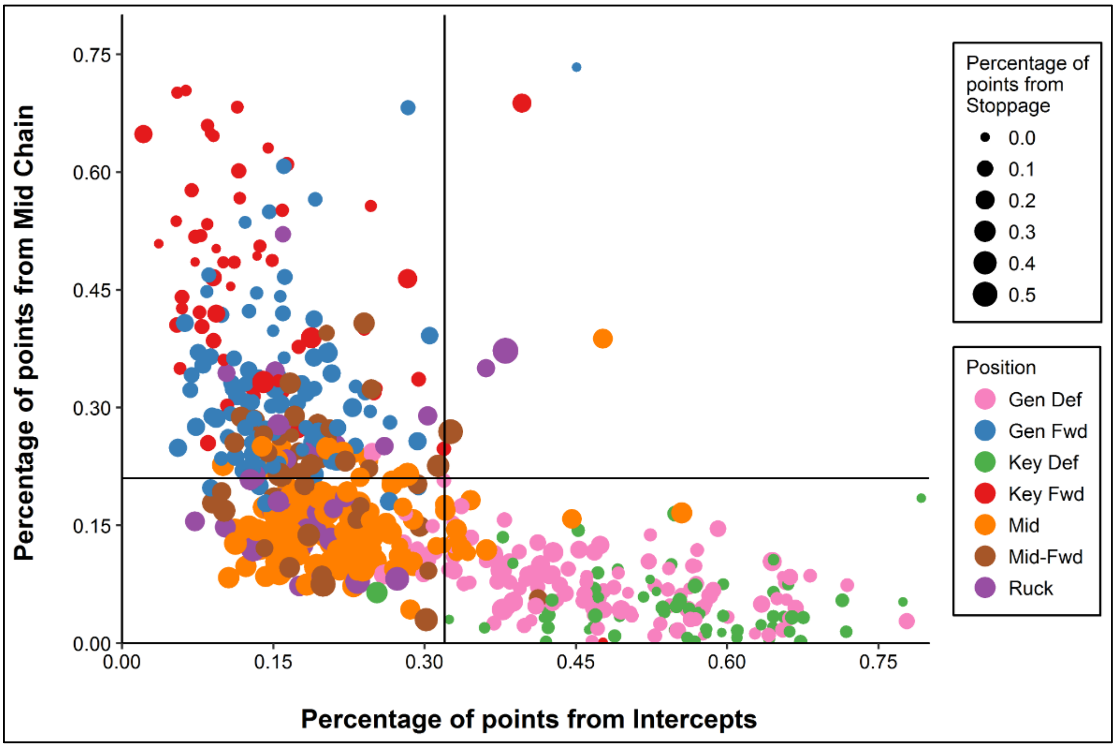

Figure 4.3 **Scatterplot displaying the relationship between Intercept, Mid Chain and Stoppage categories, expressed as relative contribution to overall rating. Each point represents a single player. Players are grouped based on their *a priori* player role classification.**

Table 4.5 Dissimilarity measures of the five most similar pairs of playing roles during the 2016 AFL season.

	Player 1			Player 2		
Dissimilarity	Name	Role	Club	Name	Role	Club
0.0299	Aliir Aliir	Gen Def	Sydney Swans	Martin Gleeson	Gen Def	Essendon
0.0443	Jack Viney	Mid	Melbourne	Brad Crouch	Mid	Adelaide Crows
0.0500	Cyril Rioli	Gen Fwd	Hawthorn	Steve Johnson	Gen Fwd	GWS Giants
0.0502	Zach Merrett	Mid	Essendon	David Zaharakis	Mid	Essendon
0.0520	Chad Wingard	Gen Fwd	Port Adelaide	Jesse White	Key Fwd	Collingwood

Table 4.6 Dissimilarity measures of individuals with the five most similar playing roles to that of Patrick Dangerfield (Midfielder, Geelong Cats), during the 2016 AFL season.

Dissimilarity	Name	Role	Club
0.1009	Jarryd Lyons	Mid	Adelaide Crows
0.1042	Dylan Shiel	Mid	GWS Giants
0.1054	Shane Edwards	Mid	Richmond
0.1010	Shaun Grigg	Mid	Richmond
0.1111	Ryan Bastinac	Mid	Brisbane Lions

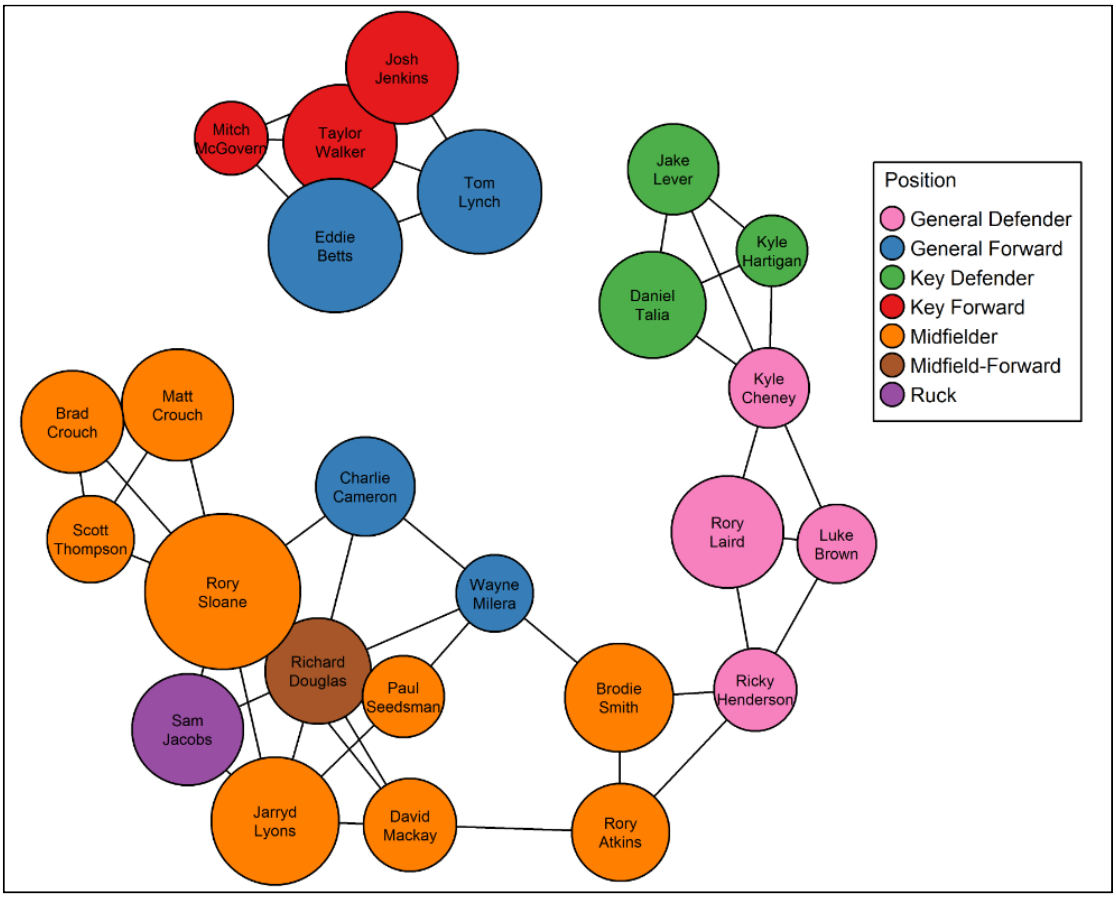

Figure 4.4 **Network plot of the Adelaide Crows squad for the 2016 season. Each player is connected with their three most similar players in the squad, as determined by the Euclidean distances. Players are coloured based on their role classification. Size is a measure of each player's average absolute AFL Player Rating.**

4.5 Discussion

This study aimed to identify the extent to which performance profiles could be used to both classify players into *a priori* determined player role categories, and determine the level of similarity between the playing styles of each individual player competing within the AFL. Two separate analyses were used to develop models addressing these aims. Modelling player role through multiple approaches (supervised and unsupervised, respectively) enables an understanding of player identification relative to that of both generalisable playing roles, as well as relative to other individual players. For the analyses, relative instead of absolute values were used to avoid a scenario whereby high-scoring players were intuitively clustered together, thus limiting the practical utility of the exercise. The relative proportion of ratings points acquired from each of the AFL Player Rating categories provides more context to player roles and player similarity within the AFL and could be used for team and squad selection.

The classification tree model (Figure 4.2) revealed the relative category contribution levels most indicative of player role classification. Notably, it displays that each of the categories relating to ball winning (stoppages, mid chain and intercepts) are included in the model, whilst none relating to ball use (run and handball, field kicks, shots at goal and kick ins) are included; thus indicating the importance of how a player wins the balls on player role classification. The model results also reflect what is seen in the scatterplot visualisation (Figure 4.3) and the descriptive statistics (Figure 4.1), but provide further detail into the distinction between the classifications of each of the seven player role categories. Specifically, key defenders typically acquire more ratings points from spoils than general defenders; this is consistent with findings previously found in elite junior AF (Woods, Veale, et al., 2018). It also highlights that hitouts are a defining category for rucks, which is expected as rating points from this category are almost exclusively acquired by ruckman (as defined by the player role description of a ruck in Table 4.1). Furthermore, stoppages are the defining category for determining the classification between midfield-forwards, general forwards and key forwards. Although, both general and key forwards are not noted for winning points from this category, the distinction is likely due to stoppages (like intercepts) being a category in which negative points are not attributed to, producing lower intra-role variability. This is evident by the lower relative standard deviations seen for stoppages in Figure 4.1.

With respect to the other player roles, the classification matrix (shown in Table 4.4) outlined that midfield-forwards had a relatively low classification rate. This is perhaps unsurprising as the midfield-forward classification is a dynamic role used to classify players who split their time between the forward line and the midfield (description outlined in Table 4.1). Champion Data's distinction of players who are classified as a midfield-forward, as opposed to a midfielder or a general forward, is dictated by the relative time spent in certain regions of the ground. The low classification rate in midfield-forwards and to a lesser extent rucks, begs the question as to whether introducing further player roles may improve classification accuracy. For example, almost all of the misclassified ruckman were classified as key forwards (11 of 13). Previous research has eluded that key forwards often share a proportion of the ruckman's main responsibility in competing for hitouts at stoppages (Veale, Pearce & Carlson, 2007). A classification could be introduced to identify those who play a role which encompasses the main actions performed by both a key forward and a ruck.

The Euclidean distance measures provide practical objective support for decisions regarding player selection and recruitment in an applied setting. The outline of players most similar to one another within a specific AFL club's playing list highlighted that players with completely different absolute ratings could be identified as similar in the way they perform. This application may be ideal for supporting week-to-week match selection when looking to replace an injured player. Similarly, it may be used to support list management decisions to identify whether specific gaps will arise on their clubs playing list, or whether there are already suitable replacements, in the case of long-term injuries or retirement of players. In contrast, including all prospective players in the model, and identifying those most similar to a specific individual could be used for list management purposes, when looking to identify players similar to that of an already listed or overly expensive, thus unattainable player. Both the methodology and findings of this unsupervised model provide practical alternates to that of similar models in AF (Jackson, 2016b).

Although the AFL Player Ratings metric has not been extended for use outside of the AFL, the findings of this study reflect notions alluded to in other research suggesting that the use of more tailored technical skill indicators could be utilised in order to objectively recognise unique player attributes, and to classify playing roles (Woods, Veale, et al., 2018). Until a point when this data becomes available for AFL feeder competitions (i.e., national under 18 championships, and second-tier state leagues), AFL organisations should look to report on, and analyse, similar specific performance indicators, in order to improve their ability to identify player roles and provide decision support.

A limitation of this study should also be noted. Champion Data's player classifications are determined relative to a set of fixed criteria, and can change throughout the course of the season. In this study, the *a priori* classifications used for player roles were based on each player's classification at the conclusion of the season. Thus, there is no way to account for a player's within season role variations. This includes players who may have changed their role completely part may through the season, as well as those who frequently split their game time between the roles of two of the *a priori* player role classifications. Although this may have reduced the overall classification rate, it may shape the performance profile of these individuals within the unsupervised model to highlight their ability to play multiple roles. In order to improve the accuracy of the player role classifications, and to determine the extent to which individual classifications vary across the season, future work may look to classify each individual's role based on that which they played during each individual match, rather than across a full season. Furthermore, future research could also focus on the development of additional player role classifications to more accurately identify groups of players whose roles do not fit the current classifications.

4.6 Conclusion

The models developed in this study provide evidence that player role can be determined using performance data relating to player actions. Firstly, the supervised model found the role classifications of key forwards, midfielders and general defenders the easiest to objectively classify, whilst the dynamic midfield-forward role more difficult to define. Specifically, the model outlined the importance of how a player wins the ball on player role classification. Secondly, the unsupervised model highlighted that using relative proportions of ratings can be used to highlight similarity in performance for players with completely different absolute ratings. Finally, the models produced in this study provide AFL organisations with objective applications that could be used to support decisions regarding player roles.

CHAPTER FIVE – STUDY III

Chapter Overview

Chapter Five is the third of the studies contained in this thesis. The study looks to develop two separate models to objectively benchmark AFL player performance, and to identify stages of peak performance and specific breakpoints longitudinally. It achieves this aim by considering a player's age, experience, positional role, and both draft type and round in which they were selected.

This chapter contains an abstract (section 5.1), introduction (section 5.2), methods (section 5.3), results (section 5.4), discussion (section 5.5) and conclusion (section 5.6) sections. The content of this chapter was published in Frontiers in Psychology, within the Research Topic: Performance Analysis in Sport (McIntosh, Kovalchik & Robertson, 2019b). Additionally, preliminary work relating to the study was presented at the World Congress of Performance Analysis of Sport XII.

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Multifactorial Benchmarking of Longitudinal Player Performance in the Australian Football League

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This study aimed to develop a model to objectively benchmark professional Australian Rules football (AF) player performance based on age, experience, positional role and both draft type and round in the Australian Football League (AFL). The secondary aims were to identify the stage of peak performance and specific breakpoints in AF player performance longitudinally. AFL Player Ratings data were obtained for all players (n = 1052) from the 1034 matches played during the 2013–2017 seasons, along with data pertaining to the abovementioned player characteristics. Two separate linear mixed models revealed that all factors influenced player performance, with age and experience the strongest in each model, respectively. *Post hoc* Tukey tests indicated that performance was affected by age at each level up until the age of 21 (effect ranging from 0.98 to 3.70 rating points), and by experience at the levels 1–20 and 21–40 matches in comparison to all higher levels of experience (effect ranging from 1.01 to 3.77 rating points). Two segmented models indicated that a point of marginal gains exists within longitudinal performance progression between the age levels 22 and 23, and the experience levels 41–60 and 61–80 matches. Professional sporting organisations may apply the methods provided here to support decisions regarding player recruitment and development.

Keywords: decision support, performance analysis, data visualisation, player evaluation, team sport

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INTRODUCTION

Identifying when peak performance typically occurs in athletes is an important consideration within professional team sport organisations. Specifically, at what point in an athletes career are they likely to reach their peak. Such information can be used to inform contracting as well as the make-up of team rosters. The identification of peak performance can be measured longitudinally on various time series including the age of an athlete, amount of years within a professional program and their match's experience (Torgler and Schmidt, 2007). Additionally, various type of peaks have been investigated within the notational team sport literature, including when an athlete is at their physiological peak (Reilly et al., 2000), when they reach their peak market value (Kalén et al., 2019), as well as when their on-field performance is at its peak (Fair, 2008; Bradbury, 2009; Dendir, 2016). Although peak performance has been well documented longitudinally for age in individual sporting events (Schulz and Curnow, 1988; Allen and Hopkins, 2015; Longo et al., 2016), its identification within team sports may be more complex. This complexity primarily arises due to the difficulty objectively outlining individual performances given that there are no quantifiable outcomes which occur directly from player actions in most team sports (Travassos et al., 2013; Robertson et al., 2015). Additionally, there is an increased importance of specific skill demands required in team based sports, including non-physical abilities such as experience and strategic knowledge (Bradbury, 2009), as well as the complexity of accounting for differences individual playing roles.

Despite this, individualised assessment of match performance in professional team sports is commonplace. This includes both subjective assessments of performance, as made by team coaches, management and within the media, as well as objective assessments made through data-driven techniques (Carling et al., 2008; Bonney et al., 2019). Although subjective assessments are often made by those in influential decision making positions (i.e., coaches), there has been a change within professional sport organisations toward supporting decisions with objective assessments (Maymin, 2017). Concurrently, there has been an increasing amount of data-driven techniques proposed in literature regarding assessing individual player performance in team sport on a quantitative scale. Some examples include Radovanović et al. (2013) who developed a player efficiency rating, which objectively measures a player's productivity in basketball based on player actions such as points, assists, rebounds, steals and turnovers, and their outcomes. Similarly, McHale et al. (2012) developed a player performance index to rate the performance of players in the top two leagues of English soccer on a quantitative scale including items such as match contributions, winning performance, match appearances, goals scored, assists, and clean sheets.

Australian Rules football (AF) is a dynamic invasion team sport played between two opposing teams consisting of 22 players each (18 on the field and four interchange). In the elite competition of AF, the Australian Football League (AFL), players can be drafted to a professional club and begin playing as early as the age of 18, with various players managing to continue playing into their middle-to-late thirties. There has been a substantial amount of research developed in AF to identify the physical and technical characteristics of individual players with respect to match performance (Young et al., 2005; Veale et al., 2008; Mooney et al., 2011; Tangalos et al., 2015; Woods et al., 2016). However, to our knowledge there has been no research examining longitudinal player performance in professional AF. However, various studies exist in the wider notational sport literature which investigate longitudinal player performance, predominantly on identifying the age at which peak performance occurs. Examples include Dendir (2016), who used mixed effects models, and identified that the peak age of performance in the top four professional soccer leagues varied between 25 and 27, depending on position. Kalén et al. (2019) similarly looked to identify the peak age of performance in professional soccer. Using a one-way ANOVA and linear regression they found that a significant longitudinal shift in peak age has occurred from 24.9 years in 1992–1993 to 26.5 years in 2007–2018. Using a random effects model Bradbury (2009) investigated peak performance of skills in baseball, finding that overall performance peaks around the age of 29. Specifically, athletic skills such as hitting and running peak earlier, whilst skills based on experience and knowledge such as drawing walks, peak later. Fair (2008) also examined the estimated age effects in baseball. Using a non-linear fixed effects regression, they found that the peak age and begin of decline in performance occurred around the age of 26 years for pitchers, and 28 years for batters.

In the abovementioned studies, both Dendir (2016) and Fair (2008) emphasise that considerations or assumptions must be made about other factors when assessing longitudinal player performance. Notably, a player's position and their level of experience. In addition to these factors, another consideration is the position at which players are selected in their respective draft. Studies such as O'Shaughnessy (2010) have looked to develop a valuation system for the AFL National Draft, indicating that earlier selections are valued more highly on the basis that clubs can select the best available player in the pool.

In addition to identifying peak player performance, longitudinal research has also looked to identify whether specific changes in trends occur within a time series. Within sport performance, this research has consisted of identifying longitudinal changes in trends of physical performance (Fransen et al., 2017; Towlson et al., 2018), game related statistics (Lorenzo et al., 2019), and gameplay (Wolfson et al., 2015; Woods et al., 2017), as well as whether external factors such as a player's contract status effect performance (Gómez et al., 2019). Though this type of model has not been applied to player performance in team sports, the use of this procedure would allow for the construction of a model to identify whether a breakpoint in longitudinal player performance exists.

The ability to benchmark player performance longitudinally is inherently valuable to many sports, and could be used to support organisational decisions regarding player contracting, recruitment and development (Kalén et al., 2019). In the AFL, there is a large emphasis on decisions relating to player contracting and recruitment as clubs are confined in their ability to remunerate players by a salary cap. Decisions relating to player development are also vital, as clubs do not have the opportunity to attain additional players within season. As such, the ability to inform these decisions based on comparisons of player performance against model-expected performance, or the ability to forecast future performance is advantageous. Further, a greater understanding of when performance progression is at its maximum, or conversely when progression is expected to deteriorate, could have important implications for the type of skill development implemented for specific individuals.

There are various player performance measures which are produced commercially within the AFL. The "AFL Player Rankings" is produced by statistics provider Champion Data Pty Ltd., measures player performance by awarding players a fixed value for specific performance actions. The values for these actions were determined relative to their observed relationship to team winning margin (Herald Sun, 2016). Alternatively, the "AFL Player Ratings", which is also produced by statistics provider Champion Data Pty Ltd., measures player performance based on the principle of field equity. In this metric, points are awarded to (or deducted from) a player based on contextual information relating to each possession, relative to how much their actions increase or decrease their team's expected value of scoring next (Jackson, 2009; McIntosh et al., 2018).

The primary aim of this study was to develop a model to objectively benchmark AFL player performance whilst considering their age, experience, positional role and both draft type and round in which they were selected. The secondary aims were to identify the stage of peak performance and specific breakpoints in player performance longitudinally. To achieve these, this study will consider the player characteristics and model types outlined in the abovementioned literature.

MATERIALS AND METHODS

Data

The AFL Player Ratings were utilised as the objective measure of player performance in this study due to its validity and its equity-based nature (Jackson, 2009; McIntosh et al., 2018). In this metric, a player's overall match performance is measured by the overall change in equity that is created by that player's actions during the course of a match (Jackson, 2009). The change in equity is determined by expected value of their team scoring next. These expected values are based on contextual information relating to possessions (i.e., field position, pressure from opponents, possession outcome) collected from all AFL matches preceding back to the 2004 season (Jackson, 2009).

These AFL Player Ratings were obtained from Champion Data Pty Ltd. for all 1034 matches played throughout the 2013–2017 AFL seasons. This included 22 matches played by each team during the regular season rounds, as well as a total of nine matches played throughout the finals series each season. One match was abandoned prior to play during the 2015 season. The AFL Player Ratings data were expressed as a mean season rating for each player across each of the five seasons. The sample included a mean of 3.15 seasons per player (±1.55 SD) among 1052 unique players, giving a total sample size of $n = 3317$.

Data pertaining to player characteristics were also collected in order to assess their relationship with performance. Age (determined by the players age at 31st December of the previous year), experience (determined by the number of AFL matches played, independent of seasons, and taken at the conclusion of each season), positional role classification (determined by Champion Data's classification at the conclusion of each season; classifications outlined in **Appendix Table A1**) and the characteristics of the draft (draft types outlined in **Appendix Table A2**) in which each player was first selected by an AFL club were all collected as descriptive variables. Prior to data collection, the study was approved by the relevant human research ethics committee.

Data Analysis

For modelling purposes, various aspects of the data required transformation. All characteristics were considered as categorical variables. Categorisation levels for age and experience were determined by evaluating the change in Akaike's Information Criterion for differing amounts of categories (Akaike, 1987). Sixteen categories for both characteristics were chosen by identifying the minimum number of categories at which the point gains in Akaike's Information Criterion became minimal (<10). This allowed for discretisation that balanced model fit and complexity (Bozdogan, 1987). Age was expressed as integer categories (18, 19, 20, . . ., 33+), where due to the limited sample size of players aged 33–40 years, data were combined into one category. Experience was expressed in intervals of 20 matches (1–20, 21–40, 41–60, . . ., 301+), where all players with 301 or more matches experience were similarly combined into one category due to the limited sample size. Categorisation levels for draft selection were arbitrarily expressed over ten levels relative to the type and round in which they were first selected by an AFL club (five levels for National Draft rounds 1 to 5+, four levels for Rookie Draft rounds 1 to 4+, and one category for the Preseason Draft). Due to the limited sample size of players drafted after round five of the national draft, after round four of the rookie draft, and in total from the preseason draft, data were combined into one category for each draft type. Positional role classification was expressed across the seven levels as determined by Champion Data (general defender, key defender, general forward, key forward, midfielder, midfield-forward, and ruck).

Further, as part of the entry concessions given to newly established clubs, the Gold Coast Suns and the Greater Western Sydney Giants, 45 players from the dataset were drafted to AFL clubs prior to the 2011, 2012, and 2013 AFL seasons via non-traditional draft methods. Considering the circumstances of these concessions, all players drafted via methods of zone selection, as an underage recruit, through the AFL mini-draft, as an AFL initiative or were pre-listed by an AFL club ($n = 42$), were considered as first round selections within the national draft. Further, those drafted after being overlooked in the prior year's national draft ($n = 3$) were considered as first round selections within the rookie draft.

Statistical Analysis

Descriptive statistics for age and experience, and how they relate to AFL Player Ratings [mean ± 95% confidence intervals (CI)] were obtained. The number of matches played per season and proportion of players were also collected and plotted across age and experience. Prior to undertaking the main analyses, Spearman's correlation analyses were employed to determine the extent of collinearity between each of the four player characteristics. This analysis was undertaken using the *Hmisc* package (Harrell, 2017) in the R statistical computing software version 3.3.2. (R Core Team, 2016). This analysis revealed a strong association between age and experience ($r = 0.83$), whilst all remaining associations were weak ($r < 0.15$). As a result, separate models were created throughout the further analyses, utilising age and experience as the independent variables in each.

To determine the extent to which these characteristics affect performance, linear mixed models were applied using the *lme4* package (Bates et al., 2015). Two separate models were created, each incorporating either age or experience, with all other factors included in both. This particular approach was used to control the variability created by the repeated measures data on each player. Specifically, the factors of interest (age, experience, positional

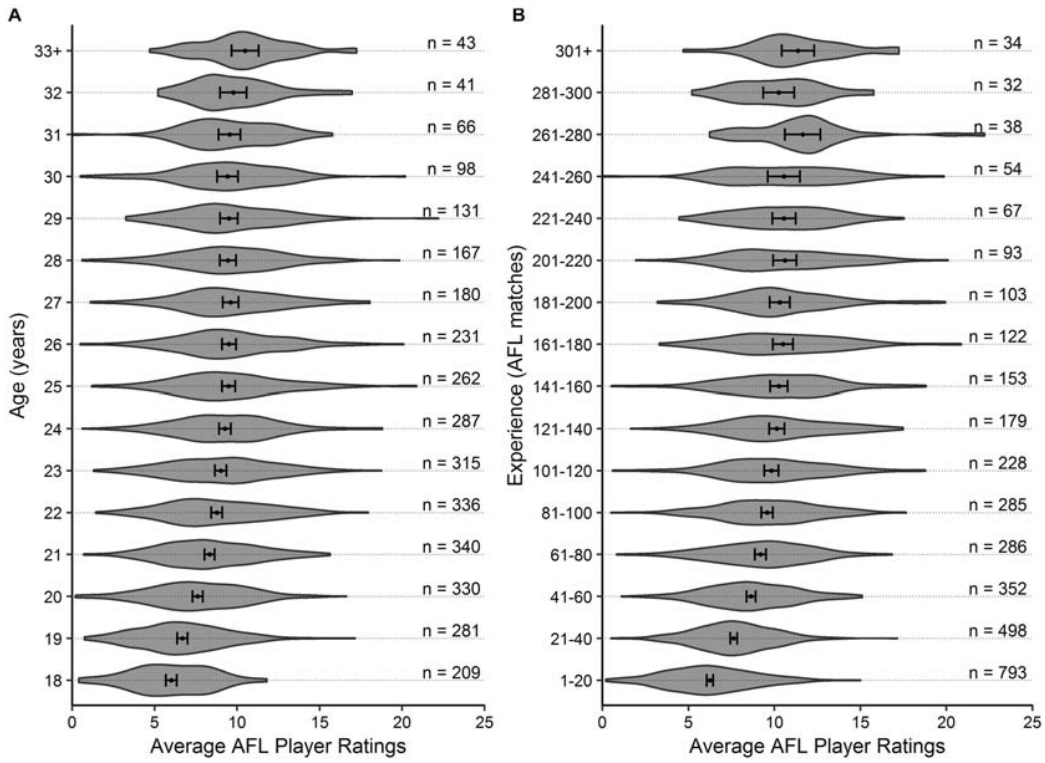

FIGURE 1 | Violin plot outlining the density of the average AFL Player Ratings (±95% CI) for **(A)** age and **(B)** experience, respectively. The number of observations in each group are outlined.

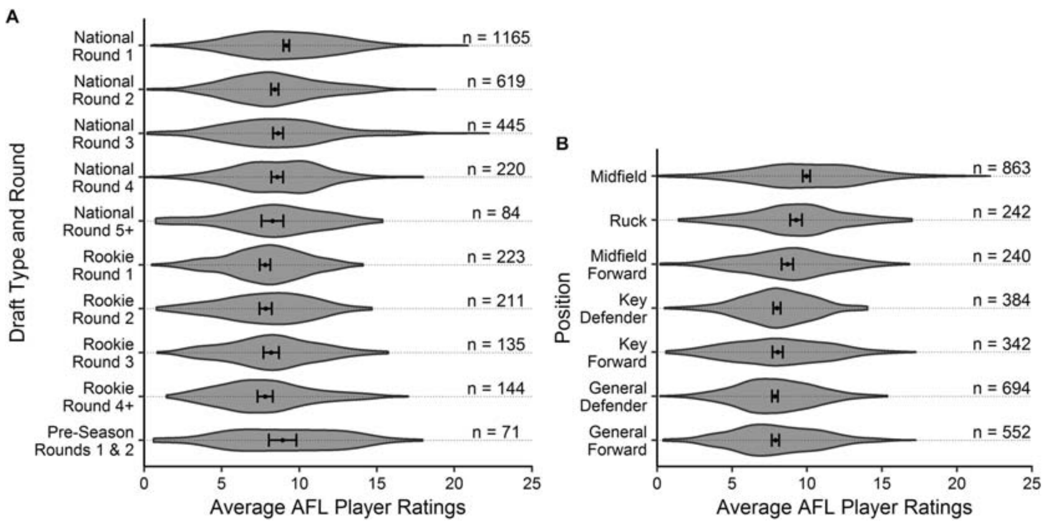

FIGURE 2 | Violin plot outlining the density of the average AFL Player Ratings (±95% CI) for **(A)** draft and **(B)** positional role, respectively. The number of observations in each group are outlined.

role, and draft selection) were treated as fixed effects, and player as a random effect in both models. Each model took the form of:

$$PR_{ps} = \beta_0 + \beta_1 X_{ps} + \beta_2 Y_{ps} + \beta_3 Z_p + \propto_p + \varepsilon_{ps}$$

where PR_{ps} is the AFL Player Rating average of player p in season s (s = 2013–2017). β_0, β_1, β_2, and β_3 are fixed coefficients, and X, Y, and Z are observed covariates. In model (1), X_{ps} and Y_{ps} represent the player's age and positional role for the corresponding season, respectively, whilst Z_p represents the category outlining the player's draft selection, which stays consistent between seasons. The parameter $\propto_p$ is a player random effect, which makes the intercept of the model specific to each player and allows for individualised performance projections. The player random effect is treated as constant across seasons and each effect is a draw from a normal distribution with equal variance for all players. The parameter ε_{ps} denotes the player-season residual error. Model (2) takes the exact same form as model (1), however, X_{ps} instead represents a player's experience for the corresponding season.

Based on the fixed effects estimates, benchmark levels of performance were plotted ($\propto_p$ = 0) for age and experience, respectively, where means and 90% prediction intervals (PI) are averaged over the levels of positional role and draft for both. A *post hoc* Tukey test was performed to adjust for multiple comparisons, and to determine whether performance was different within each level of age and experience, and thus identifying a hypothesised breakpoint in performance. To further assess whether a breakpoint exists in each of the linear mixed models, a segmented model (or "piecewise linear model") was fit to the data to estimate if a change in the trend of the data occurs. This analysis was undertaken using the *segmented* package (Muggeo, 2008). As a result of the *post hoc* Tukey tests, we specified the levels 22 for age, and 41–60 for experience as the hypothesised break points. Within this analysis, these points are used as starting points for which the model uses to estimate

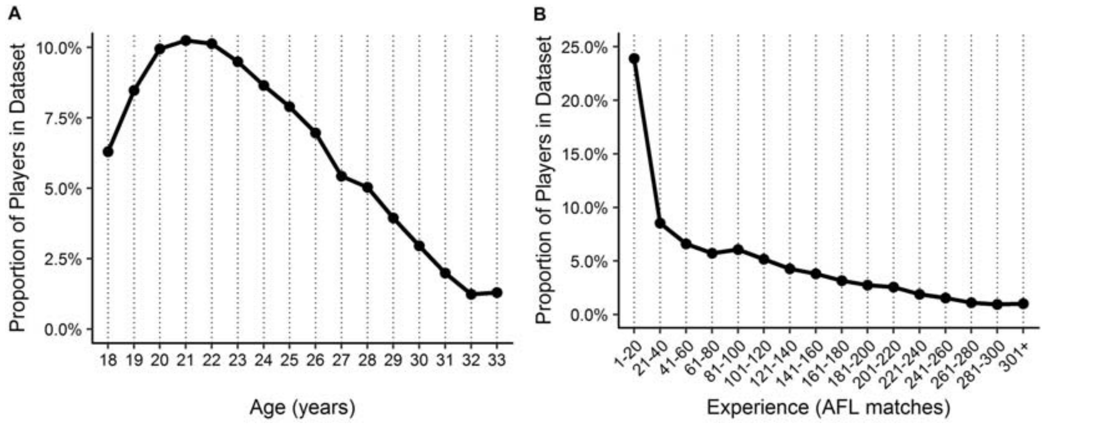

FIGURE 3 | Proportion of players in the dataset by **(A)** age and **(B)** experience.

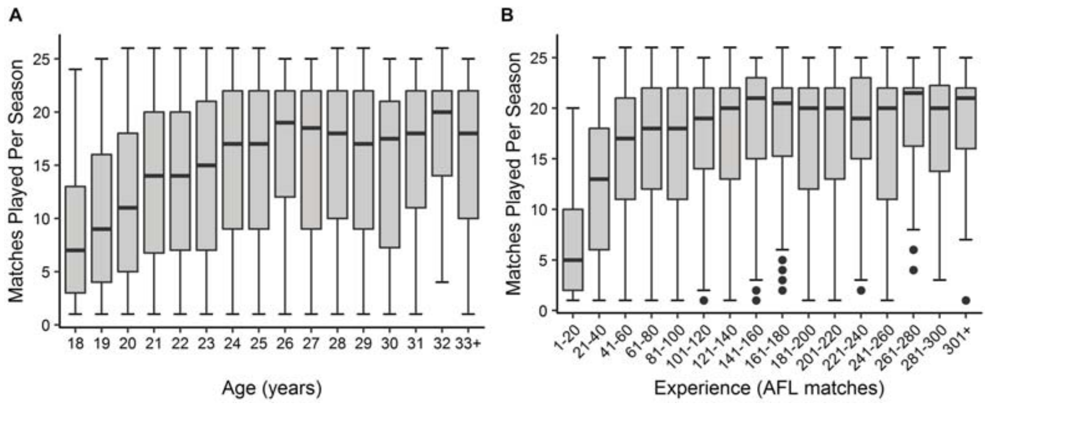

FIGURE 4 | Boxplot outlining the distribution of matches played per season by players in each level of **(A)** age and **(B)** experience.

TABLE 1 | Model (1) fixed effect regression coefficients outlining the estimated difference in rating points from the reference level of each factor.

	Regression coefficients (±SE)
(Intercept)	7.11 (0.23)
Age 19	0.98 (0.20)
Age 20	1.93 (0.21)
Age 21	2.62 (0.21)
Age 22	3.06 (0.22)
Age 23	3.32 (0.22)
Age 24	3.39 (0.23)
Age 25	3.69 (0.24)
Age 26	3.70 (0.25)
Age 27	3.68 (0.26)
Age 28	3.31 (0.27)
Age 29	3.18 (0.29)
Age 30	2.80 (0.32)
Age 31	2.48 (0.37)
Age 32	2.56 (0.44)
Age 33+	2.46 (0.47)
Positional role Gen Def	−1.25 (0.17)
Positional role Gen Fwd	−1.13 (0.17)
Positional role Key Def	−1.128 (0.23)
Positional role Key Fwd	−1.79 (0.23)
Positional role Mid Fwd	−0.79 (0.19)
Positional role Ruck	−0.38 (0.29)
Draft National 2	−0.78 (0.23)
Draft National 3	−0.74 (0.25)
Draft National 4	−0.94 (0.32)
Draft National 5+	−1.21 (0.47)
Draft Rookie 1	−1.47 (0.32)
Draft Rookie 2	−1.62 (0.33)
Draft Rookie 3	−1.56 (0.39)
Draft Rookie 4 +	−1.75 (0.38)
Draft Preseason	−1.03 (0.57)

Reference level for each factor were: age 18, positional role midfield, Draft National 1.

TABLE 2 | Model (2) fixed effect regression coefficients, outlining the estimated difference in rating points from the reference level of each factor.

	Regression coefficients (±SE)
(Intercept)	7.43 (0.18)
Experience 21–40	1.31 (0.14)
Experience 41–60	2.32 (0.16)
Experience 61–80	2.79 (0.18)
Experience 81–100	3.19 (0.18)
Experience 101–120	3.38 (0.20)
Experience 121–140	3.48 (0.22)
Experience 141–160	3.39 (0.23)
Experience 161–180	3.77 (0.25)
Experience 181–200	3.43 (0.27)
Experience 201–220	3.53 (0.29)
Experience 221–240	3.32 (0.33)
Experience 241–260	3.02 (0.36
Experience 261–280	3.74 (0.43)
Experience 281–300	2.46 (0.47)
Experience 301+	3.02 (0.52)
Position Gen Def	−1.17 (0.16)
Position Gen Fwd	−1.24 (0.16)
Position Key Def	−1.07 (0.21)
Position Key Fwd	−1.49 (0.22)
Position Mid Fwd	−0.74 (0.19)
Position Ruck	−0.12 (0.26)
Draft National 2	−0.54 (0.20)
Draft National 3	−0.30 (0.23)
Draft National 4	−0.27 (0.29)
Draft National 5+	−0.75 (0.42)
Draft Rookie 1	−0.89 (0.29)
Draft Rookie 2	−0.85 (0.30)
Draft Rookie 3	−0.46 (0.35)
Draft Rookie 4 +	−0.71 (0.34)
Draft Preseason	−0.49 (0.51)

Reference level for each factor were: experience 1–20, positional role midfield, Draft National 1.

breakpoints. A level of significance was accepted at $p < 0.01$ in all analyses.

RESULTS

Descriptive statistics are outlined in **Figures 1**, **2** for age and experience, and positional role and draft, respectively. **Figure 3A** highlights that the proportion of players competing in the AFL is at its highest at ages 20–22, and then declines with each consecutive age level thereafter. Further, **Figure 3B** highlights that the proportion of players is highest in the least experienced group (20 matches or less), and similarly declines with each consecutive category level of experience thereafter. On the contrary, **Figure 4** indicates that the average number of matches played per season increases with both age and experience.

Results of the linear mixed models revealed that all factors affected levels of performance in both models at $p < 0.01$. Model (1) produced a root mean square error of 1.77 and Chi-square values of 356.9 for age, 98.7 for positional role and 57.1 for draft. Comparatively, model (2) produced a root mean square error of 1.82 rating points and Chi-square values of 523.5 for experience, 100.4 for positional role and 21.7 for draft. The values indicate that age and experience had the largest influence on performance in each of the models, respectively, followed by positional role. **Tables 1**, **2** outline the fixed effect coefficients (β_0, β_1, β_2, and β_3) for each factor level of the characteristics in each of the respective models.

Results of the *post hoc* Tukey test indicated that performance was affected by age at various age levels up until the age of 21 (mean differences ranged from 0.98 to 3.70 player rating points). However, no two levels above the age of 21 were seen to exhibit different levels of performance. For experience, differences were seen at the levels of 1–20 matches and 21–40 matches in comparison to all higher levels of experience (mean differences ranged from 1.01 to 3.77 player rating points), and for various experience levels in comparison to 41–60 matches. No differences were seen between any levels above this for experience.

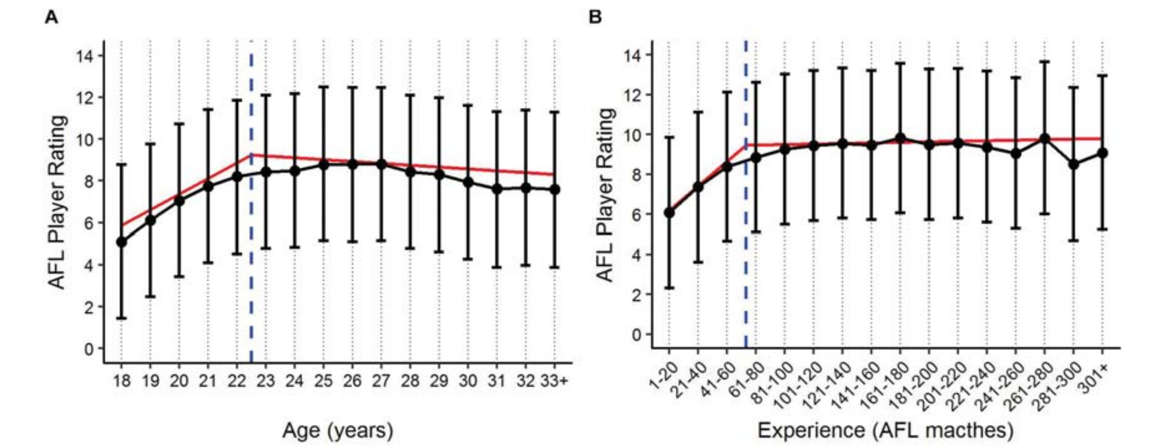

FIGURE 5 | Benchmark levels of AFL Player Ratings (±90% PI) by **(A)** age and **(B)** experience, based on the fixed effects estimates. Blue *x*-axis intercept lines represent the level at which the breakpoint in performance occurs for both age and experience, respectively. Red regression lines represent the multiple linear fits of the segmented models.

The segmented models identified a breakpoint in performance for both age and experience. The results indicate that a breakpoint in age occurs between the age levels 22 and 23, where performance is seen to increase linearly 0.75 rating points per age level prior to this breakpoint, and decline linearly 0.09 rating points per age level thereafter. The breakpoint identified for experience occurs between the levels 41–60 and 61–80, where performance is seen to increase linearly 1.24 rating points per level of experience prior to this breakpoint, and then continue to increase linearly 0.04 rating points per experience level thereafter. **Figure 5** displays the benchmark levels of performance for both age and experience, where player specific random effects (PSRE) are removed. *X*-axis intercept lines and regression lines were added to **Figure 5** to represent the level at which the identified breakpoint in performance occurs, and the change in the trend of player performance, respectively, for both age and experience.

By applying the PSRE and the fixed effect estimates from the linear mixed models, various applications can be created to benchmark player performance. For example, **Figure 6** visualises the actual past performance and future player specific expectation of performance (fit and 90% PI) for a specific player, as compared to their fixed effect estimate of performance using model (1). This application indicates the player's performance has been below the benchmark level of performance since 2014, but within the 90% PI, and is expected to remain fairly consistent in the three forecasted seasons. **Figure 7** outlines how model (1) could be used for player comparison, indicating that the player in blue is likely to perform better in each of the forecasted seasons. Further, **Figure 8** visualises the actual past performance and future player specific expectation of performance (fit only) for a specific player, using both the models based on age (blue) and experience (red).

Additionally, the PSRE provide a measure of player ranking, which adjusts for the individual fixed effects characteristics. **Table 3** outlines the top five players in each positional roles, as determined by the average of the PSRE across the two linear mixed models. Player positional role was determined by the category in which they were categorised the most frequently over the five seasons.

DISCUSSION

The primary aim of this study was to develop a model to objectively benchmark player performance whilst considering

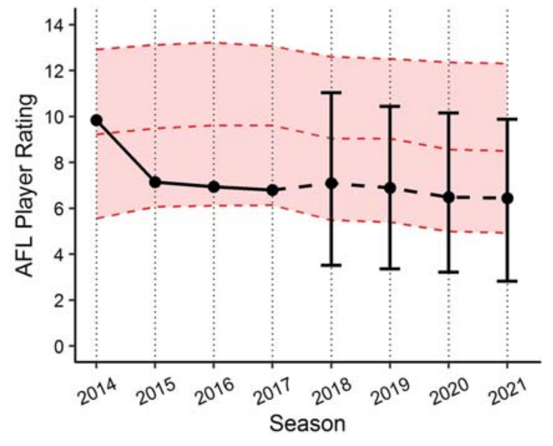

FIGURE 6 | Benchmark levels of AFL Player Ratings for a specific player using the age linear mixed model. Black lines represents actual performance to 2017 and player specific expectation (±90% PI) of performance from 2018. Red ribbon represents fixed effects estimates based on characteristics of same player.

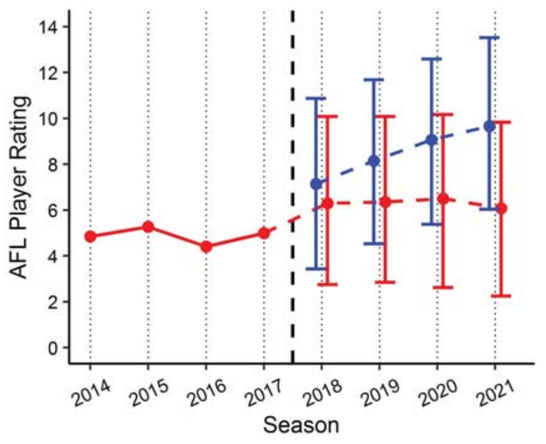

FIGURE 7 | Benchmark levels of AFL Player Ratings for two specific players using the age linear mixed model. Red line represents actual performance prior to 2017. Red and blue lines indicate player specific expectations (±90% PI) of performance from 2018 for each player. Black *x*-axis intercept line indicates point of comparison.

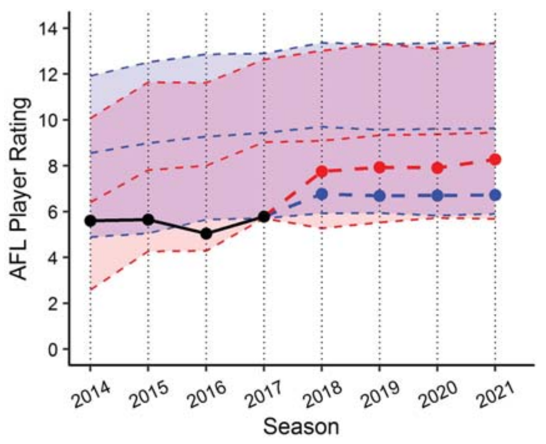

FIGURE 8 | Benchmark levels of AFL Player Ratings for a specific player using the both the age (blue) and experience (red) linear mixed models. Black line represents actual performance to 2017. Blue and red points indicate expectation of performance from 2018 using each the age and experience models, respectively. Similarly, each ribbon represents fixed effects estimates based on characteristics of same player in each model.

their age, experience, positional role, and both draft type and round in which they were selected. It also aimed to identify the stage of peak performance and specific breakpoints in player performance longitudinally. Separate linear mixed model analyses were implemented to benchmark performance based on the multifactorial fixed effects estimates. Segmented models were fit to these fixed effect estimates to determine if and where a change in the linear trend of performance progression occurs.

Visual inspection of the descriptive statistics in **Figures 1A,B** indicate that performance continues to improve throughout an AFL players career (as indicated by the gradual increase in average AFL Player Ratings for both age and experience, respectively). However, it must be noted that this type of analysis is susceptible to selection biases (Brander et al., 2014). Specifically, previous research has identified that these biases can be bought upon as a result of better-performing players typically having longer careers than other players (Bradbury, 2009; Dendir, 2016). **Figures 3**, **4** highlight this bias on the basis that player selection is a subjective identification of each clubs best performers. Specifically, **Figure 3** outlines the proportion of players in the dataset, and indicates that there are less players across the sample in older and more experienced categories, respectively; however, **Figure 4** shows that these older and more experienced players on average play more games per season. The substantially smaller interquartile ranges and presence of outliers in **Figure 4B**, as opposed to **Figure 4A**, indicates that despite showing similar increasing trends between the two distributions, there is less variance in matches played per season with respect to experience. However, this is somewhat expected due to the compounding nature of matches played per season, to total career matches. Visual inspection of the descriptive statistics in **Figures 2A**,**B** also indicates that performance differences are seen between varying levels of both draft and position, respectively. These findings align with previous literature investigating longitudinal player performance, and supports the use of a mixed model approach to account for fixed and PSRE (Bradbury, 2009; Dendir, 2016).

Each of the two linear mixed models provide context when looking to benchmark player performance longitudinally in AF. In addition to identifying a universal benchmark trend of performance longitudinally, the models produced in this study allow player specific values to be obtained, by adjusting each of the fixed effects relative to the player's characteristics in each model. These player specific benchmarks allow for both retrospective assessment of a players past performance against expected performance, as well as to forecast player performance relative to expected characteristics (assumptions must be made with regards to positional role and experience to forecast). Applications of these models have the potential to be beneficial in supporting the decision making processes within professional AF organisations. Decisions relating to player recruitment and contracting could be objectively informed by gaining an understanding of the past and future potential performance of players, which the club maybe looking to recruit, resign or remove from their current playing squad. Though the examples provided in this study feature 90% PI, clubs/organisations wanting to be more aggressive with their predictions regarding expected performance could adapt the current models to include lower PI. **Figure 6** provides a specific example of how this can be visualised. It outlines an actual player's past performance (2014–2017) and expected future performance (2018–2021), and compares this to the benchmark level of performance based on the characteristics for that player. Alternatively, **Figure 7** outlines an actual player's past performance (2014–2017) and expected future performance (2018–2021), and compares this to

TABLE 3 | Top five players in each positional role, as determined by the average of the player specific random effects (PSRE) in each of the linear mixed models.

Player	Model 1 PSRE	Model 2 PSRE	Player	Model 1 PSRE	Model 2 PSRE
General defender			**General forward**		
Zac Williams	4.09	3.14	Brent Harvey	6.18	4.74
Adam Saad	3.30	3.22	Chad Wingard	4.31	3.26
Shaun Burgoyne	3.68	2.84	Eddie Betts	4.19	3.19
Brandon White	3.04	2.57	Luke Breust	4.32	3.02
Daniel Rich	2.97	2.57	Cyril Rioli	3.43	3.00
Key defender			**Key forward**		
Jeremy McGovern	4.44	4.11	Lance Franklin	5.21	4.51
Alex Rance	3.59	2.99	Jarryd Roughead	4.23	3.66
Tom McDonald	2.87	2.16	Justin Westhoff	4.22	3.10
Harris Andrews	3.04	1.87	Josh J. Kennedy	3.73	3.02
Josh Gibson	2.94	1.51	Jack Gunston	3.68	2.99
Midfielder			**Midfield-forward**		
Gary Ablett	8.29	6.96	Robbie Gray	4.75	3.76
Patrick Dangerfield	6.96	6.30	Dayne Zorko	3.71	3.88
Nat Fyfe	6.61	5.77	Sam Menegola	3.30	4.11
Scott Pendlebury	6.09	5.60	Christian Petracca	3.53	3.42
Marcus Bontempelli	5.44	4.49	Luke Dahlhaus	3.82	2.72
Ruck					
Todd Goldstein	4.70	3.68			
Nic Naitanui	4.29	3.57			
Sam Jacobs	3.60	2.19			
Aaron Sandilands	3.95	1.83			
Shane Mumford	3.52	1.94			

Player positional role determined by the category in which they were categorised the most frequently over the five seasons.

the expected future performance (2018–2021) of a player who is yet to be drafted.

Though the identified breakpoints found in each model differ marginally to the findings of the *post hoc* Tukey test, both analyses indicate that there is a distinct change in the trend of player performance occurring in each model, occurring at around the age 22, and experience level 41–60, respectively. Specifically, they indicate that this change in the trend represents a point of marginal gains within each of the model, such that once these levels are reached the benchmark level of player performance is expected to somewhat plateau. This indication of marginal performance gains beyond these respective levels could have useful implications for both player development and player recruiting/contracting within professional AF. For example, clubs may look to persist with selection of players who are yet to reach these points of marginal gains (as opposed to older/more experienced players of similar ability), knowing that match opportunities are potentially more detrimental to development of the younger/less experienced players. In regards to player recruiting and contracting, clubs could look to use these breakpoints as an indication of whether the performance of current players and/or potential recruits is likely to continue to improve, or whether their performance has reached a point of marginal gains. Though only one breakpoint was identified for each model in this study, clubs/organisations wanting to further explore the longitudinal performance trends could adapt the current methodology to identify whether multiple breakpoints exist.

Despite minor differences, both the models measured longitudinally on each age and experience might be used for different operational purposes based on the preferences of the organisation. For example, due to the reliance of match opportunity for the model based experience, applications of this model may be more suited to benchmark the performance of players who have experienced long-term injuries or are mature aged recruits. Conversely, for those who have had sufficient match opportunities, the models based on age may be more suitable due to the more progressive nature of age as an independent variable. **Figure 8** visualises this difference in the models through benchmarking the expected performance of a specific older age, but lowly experienced individual, using both models.

In addition to providing benchmark levels of performance, the models produced in this study also provide an indication of the point at which peak performance occurs longitudinally.

Specifically, the findings imply that on average players reach their peak around the age of 22, or 60 matches experience. In comparison to previous literature, this point at which the average player reaches their peak age is younger than what has been identified in other dynamic team sports such as soccer (Dendir, 2016). Though this peak is identified earlier, there was no substantial drop-off in performance noted in this study, indicating that that peak performance in AF may be better outlined by a peak range. There is no literature available to make these comparisons in relation to a player's match experience.

The PSRE outlined in each of the mixed models could also be used to rank players across the 2013–2017 seasons. Specifically, this type of ranking would be more generalisable than other ranking measures that do not adjust for fixed effects such as those used in our model. Thus it allows comparisons to be made between players across different ages, levels of experience, positional roles and draft selections. **Table 3** outlined the top five players in each positional role. The table indicated that despite accounting for position, the top three midfielders still exhibited higher PSRE than any other players. As an indication of the face validity for these random effects to be used to rank players, each of these three outlined individuals have won the AFL's award for the fairest and best player for one of the five seasons included in the dataset (Gary Ablett in 2013, Nat Fyfe in 2015 and Patrick Dangerfield in 2016).

Some limitations of this study should also be noted. Though mixed model approaches have been supported in previous literature to account for the fixed and random effects associated with longitudinal player performance; there is also an inherent understanding that the decline in performance after peak is often underestimated as a result of athlete drop out. For example, only the most successful athletes continue to get renewed playing contracts, and are subsequently selected to play at the elite level. Thus meaning that there is likely some level of performance deterioration that goes unnoticed by the model beyond certain ages/levels of experience. Another limitation is that the methodology could include additional metrics, such as time on ground or spatiotemporal data, potentially allowing for further explanation of the results. Future work in dynamic team sports should focus on the continual development of improving objective player performance rating models, as well as decision support applications to assist with operational decision-making in professional sporting organisations. In AF specifically, the development of these objective player performance rating models could look to include further positioning dynamics, similar to that in other team sports (Gonçalves et al., 2017; Memmert et al., 2017).

CONCLUSION

This study produced two types of models benchmarking player performance in the AFL. The first method utilised two separate linear mixed models to identify the effect of individual characteristics on player performance. Each of these models could be used to identify how a player's performance compares to individualised benchmarks, or to forecast future potential performance. The second method utilised segmented models, finding a point of marginal gains within longitudinal performance of both age and experience. The implementation of these methodologies may provide valuable knowledge for professional AFL organisations. Implications of their use could assist with organisational decisions relating to player recruitment, contracting and development. Future work should focus on the refinement of the models produced in this study as additional seasons of data become available.

AUTHOR CONTRIBUTIONS

SM and SR conceived and designed the study. SM compiled the data, conducted the statistical analyses, and wrote the bulk of the manuscript. SR oversaw the data collection and statistical analyses, and contributed substantially to the writing of the manuscript. SK contributed significantly to the methodology, and assisted with writing of the "Materials and Methods" section.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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APPENDICES

TABLE A1 | Descriptions of the seven positional roles used in this study.

Positional roles	Description
General defender	Plays a role on opposition small-medium forwards and usually helps create play from the backline
Key defender	Plays on opposition key forwards with the primary role of nullifying his opponent
General forward	Plays predominantly in the forward half of the ground but with more freedom than a key forward
Key forward	Plays predominantly as a tall marking target in the forward line
Midfielder	Spends the majority of time playing on the ball or on the wing
Midfielder-forward	Splits time equally between the forward line and the midfield. Often lines up on the half-forward flank but plays a significant amount of time in the midfield
Ruck	Has the primary role of competing for hit-outs at a stoppage

TABLE A2 | Descriptions of the three annual draft methods to enter an AFL list.

Draft type	Club participation	Trading of picks	Further description
National draft	Compulsory draft. Each club must exercise a minimum of three selections	Picks can be traded between clubs	Players selected by a club become ineligible to be included on the primary list of any other club for a period of two seasons. For the most part this draft consists of players finishing secondary school, who have been competing in elite junior feeder competitions
Preseason draft	Non-compulsory draft	Picks cannot be traded between clubs	Players selected by a club become ineligible to be included on the primary list of any other club for a period of two seasons. For the most part this draft consists of players who missed out on selection in the National Draft
Rookie draft	Non-compulsory draft	Picks cannot be traded between clubs	Players selected become part of the clubs rookie list, and cannot compete within the AFL until being promoted to the clubs primary list. For the most part this draft consists of players who missed out on selection in the National Draft or older players from second tier competitions

In all three drafts, clubs select players in the reverse order to which they finished on the final premiership ladder in the previous AFL season. To be eligible for selection, a player must be 18 years of age before the 31st of December following the national draft selection meeting.

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DECLARATION OF CO-AUTHORSHIP AND CO-CONTRIBUTION: PAPERS INCORPORATED IN THESIS BY PUBLICATION

This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

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College: College of Sport and Exercise Science Candidate's Contribution (%): 85

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2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

Sam McIntosh Digitally signed by Sam McIntosh DN: cn=Sam McIntosh, o, ou, email=sam.mcintosh@live.vu.edu.au, c=AU Date: 2019.08.20 07:01:32 +10'00'	20/08/2019
Signature	**Date**

3. CO-AUTHOR(S) DECLARATION

In the case of the above publication, the following authors contributed to the work as follows:

The undersigned certify that:

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3. There are no other authors of the publication according to these criteria;

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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Stephanie Kovalchik	5	Assisted with methodology design. Feedback and revisions for methodology.	Stephanie Kovalchik Digitally signed by Stephanie Kovalchik Date: 2019.09.05 12:12:37 +10'00'	5/9/19
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Multifactorial benchmarking of longitudinal player performance in the Australian Football League

5.1 Abstract

This study aimed to develop a model to objectively benchmark professional Australian Rules football (AF) player performance based on age, experience, positional role and both draft type and round in the Australian Football League (AFL). The secondary aims were to identify the stage of peak performance and specific breakpoints in AF player performance longitudinally. AFL Player Ratings data were obtained for all players (n = 1052) from the 1034 matches played during the 2013–2017 seasons, along with data pertaining to the abovementioned player characteristics. Two separate linear mixed models revealed that all factors influenced player performance, with age and experience the strongest in each model, respectively. *Post hoc* Tukey tests indicated that performance was affected by age at each level up until the age of 21 (effect ranging from 0.98 to 3.70 rating points), and by experience at the levels 1–20 and 21–40 matches in comparison to all higher levels of experience (effect ranging from 1.01 to 3.77 rating points). Two segmented models indicated that a point of marginal gains exists within longitudinal performance progression between the age levels 22 and 23, and the experience levels 41–60 and 61–80 matches. Professional sporting organisations may apply the methods provided here to support decisions regarding player recruitment and development.

5.2 Introduction

Identifying when peak performance typically occurs in athletes is an important consideration within professional team sport organisations. Specifically, at what point in an athletes career are they likely to reach their peak. Such information can be used to inform contracting as well as the make-up of team rosters. The identification of peak performance can be measured longitudinally on various time series including the age of an athlete, amount of years within a professional program and their match's experience (Torgler & Schmidt, 2007). Additionally, various type of peaks have been investigated within the notational team sport literature, including when an athlete is at their physiological peak (Reilly, Bangsbo & Franks, 2000), when they reach their peak market value (Kalén et al., 2019), as well as when their on-field performance is at its peak (Bradbury, 2009; Dendir, 2016; Fair, 2008). Although peak performance has been well documented longitudinally for age in individual sporting events (Allen & Hopkins, 2015; Longo, Siffredi, Cardey, Aquilino & Lentini, 2016; Schulz & Curnow, 1988), its identification within team sports may be more complex. This complexity primarily arises due to the difficulty objectively outlining individual performances given that there are no quantifiable outcome which occur directly from player actions in most team sports (Robertson, Back, et al., 2015; Travassos et al., 2013). Additionally, there is an increased importance of specific skill demands required in team-based sports, including non-physical abilities such as experience and strategic knowledge (Bradbury, 2009), as well as the complexity of accounting for differences individual playing roles.

Despite this, individualised assessment of match performance in professional team sports is commonplace. This includes both subjective assessments of performance, as made by team coaches, management and within the media, as well as objective assessments made through data-driven techniques (Bonney, Berry, Ball & Larkin, 2019; Carling et al., 2008). Although subjective assessments are often made by those in influential decision-making positions (i.e., coaches), there has been a change within professional sport organisations toward supporting decisions with objective assessments (Maymin, 2017). Concurrently, there has been an increasing amount of data-driven techniques proposed in literature regarding assessing individual player performance in team sport on a quantitative scale. Some examples include Radovanović et al. (2013) who developed a player efficiency rating, which objectively measures a player's productivity in basketball based on player actions such as points, assists, rebounds, steals and turnovers, and their outcomes. Similarly, McHale et al. (2012) developed a player performance index to rate the performance of players in the top two leagues of English soccer on a quantitative scale including items such as match contributions, winning performance, match appearances, goals scored, assists, and clean sheets.

Australian Rules football (AF) is a dynamic invasion team sport played between two opposing teams consisting of 22 players each (18 on the field and four interchange). In the elite competition of AF, the Australian Football League (AFL), players can be drafted to a professional club and begin playing as early as the age of 18, with various players managing to continue playing into their middle-to-late thirties. There has been a substantial amount of research developed in AF to identify the physical and technical characteristics of individual players with respect to match performance (Mooney et al., 2011; Tangalos et al., 2015; Veale, Pearce, Koehn & Carlson, 2008; Woods, Joyce & Robertson, 2016; Young et al., 2005). However, to our knowledge there has been no research examining longitudinal player performance in professional AF. However, various studies exist in the wider notational sport literature which investigate longitudinal player performance, predominantly on identifying the age at which peak performance occurs. Examples include Dendir (2016), who used mixed effects models, and identified that the peak age of performance in the top four professional soccer leagues varied between 25 and 27, depending on position. Kalén et al. (2019) similarly looked to identify the peak age of performance in professional soccer. Using a one- way ANOVA and linear regression they found that a significant longitudinal shift in peak age has occurred from 24.9 years in 1992–1993 to 26.5 years in 2007–2018. Using a random effects model Bradbury (2009) investigated peak performance of skills in baseball, finding that overall performance peaks around the age of 29. Specifically, athletic skills such as hitting and running peak earlier, whilst skills based on experience and knowledge such as drawing walks, peak later. Fair (2008) also examined the estimated age effects in baseball. Using a non-linear fixed effects regression, they found that the peak age and begin of decline in performance occurred around the age of 26 years for pitchers, and 28 years for batters.

In the abovementioned studies, both Dendir (2016) and Fair (2008) emphasise that considerations or assumptions must be made about other factors when assessing longitudinal player performance. Notably, a player’s position and their level of experience. In addition to these factors, another consideration is the position at which players are selected in their respective draft. Studies such as O’Shaughnessy (2010) have looked to develop a valuation system for the AFL National Draft, indicating that earlier selections are valued more highly on the basis that clubs can select the best available player in the pool.

In addition to identifying peak player performance, longitudinal research has also looked to identify whether specific changes in trends occur within a time series. Within sport performance, this research has consisted of identifying longitudinal changes in trends of physical performance (Fransen et al., 2017; Towlson, Cobley, Parkin & Lovell, 2018), game related statistics (Lorenzo, Lorenzo, Conte & Giménez, 2019), and gameplay (Wolfson, Koopmeiners & DiLernia, 2015; Woods, Robertson, et al., 2017), as well as whether external factors such as a player’s contract status effect performance (Gómez, Lago, Gómez & Furley, 2019). Though this type of model has not been applied to player performance in team sports, the use of this procedure would allow for the construction of a model to identify whether a breakpoint in longitudinal player performance exists.

The ability to benchmark player performance longitudinally is inherently valuable to many sports, and could be used to support organisational decisions regarding player contracting, recruitment and development (Kalén et al., 2019). In the AFL, there is a large emphasis on decisions relating to player contracting and recruitment as clubs are confined in their ability to remunerate players by a salary cap. Decisions relating to player development are also vital, as clubs do not have the opportunity to attain additional players within season. As such, the ability to inform these decisions based on comparisons of player performance against model-expected performance, or the ability to forecast future performance is advantageous. Further, a greater understanding of when performance progression is at its maximum, or conversely when progression is expected to deteriorate, could have important implications for the type of skill development implemented for specific individuals.

There are various player performance measures which are produced commercially within the AFL. The "AFL Player Rankings" is produced by statistics provider Champion Data Pty Ltd., measures player performance by awarding players a fixed value for specific performance actions. The values for these actions were determined relative to their observed relationship to team winning margin (Herald Sun, 2016). Alternatively, the "AFL Player Ratings", which is also produced by statistics provider Champion Data Pty Ltd., measures player performance based on the principle of field equity. In this metric, points are awarded to (or deducted from) a player based on contextual information relating to each possession, relative to how much their actions increase or decrease their team's expected value of scoring next (Jackson, 2009; McIntosh et al., 2018b).

The primary aim of this study was to develop a model to objectively benchmark AFL player performance whilst considering their age, experience, positional role and both draft type and round in which they were selected. The secondary aims were to identify the stage of peak performance and specific breakpoints in player performance longitudinally. To achieve these, this study will consider the player characteristics and model types outlined in the abovementioned literature.

5.3 Methods

5.3.1 Data

The AFL Player Ratings were utilised as the objective measure of player performance in this study due to its validity and its equity-based nature (Jackson, 2009; McIntosh et al., 2018b). In this metric, a player's overall match performance is measured by the overall change in equity that is created by that player's actions during the course of a match (Jackson, 2009). The change in equity is determined by expected value of their team scoring next. These expected values are based on contextual information relating to possessions (i.e., field position, pressure from opponents, possession outcome) collected from all AFL matches preceding back to the 2004 season (Jackson, 2009).

These AFL Player Ratings were obtained from Champion Data Pty Ltd. for all 1034 matches played throughout the 2013–2017 AFL seasons. This included 22 matches played by each team during the regular season rounds, as well as a total of nine matches played throughout the finals series each season. One match was abandoned prior to play during the 2015 season. The AFL Player Ratings data were expressed as a mean season rating for each player across each of the five seasons. The sample included a mean of 3.15 seasons per player (±1.55 SD) among 1052 unique players, giving a total sample size of $n = 3317$.

Data pertaining to player characteristics were also collected in order to assess their relationship with performance. Age (determined by the players age at 31st December of the previous year), experience (determined by the number of AFL matches played, independent of seasons, and taken at the conclusion of each season), positional role classification (determined by Champion Data's classification at the conclusion of each season; classifications outlined in Appendix B.1) and the characteristics of the draft (draft types outlined in Appendix B.2) in which each player was first selected by an AFL club were all collected as descriptive variables. Prior to data collection, the study was approved by the relevant human research ethics committee.

5.3.2 Data analysis

For modelling purposes, various aspects of the data required transformation. All characteristics were considered as categorical variables. Categorisation levels for age and experience were determined by evaluating the change in Akaike's Information Criterion for differing amounts of categories (Akaike, 1987). Sixteen categories for both characteristics were chosen by identifying the minimum number of categories at which the point gains in Akaike's Information Criterion became minimal (<10). This allowed for discretisation that balanced model fit and complexity (Bozdogan, 1987). Age was expressed as integer categories (18, 19, 20, ..., 33+), where due to the limited sample size of players aged 33–40 years, data were combined into one category. Experience was expressed in intervals of 20 matches (1–20, 21–40, 41–60, . . ., 301+), where all players with 301 or more matches experience were similarly combined into one category due to the limited sample size. Categorisation levels for draft selection were arbitrarily expressed over ten levels relative to the type and round in which they were first selected by an

AFL club (five levels for National Draft rounds 1 to 5+, four levels for Rookie Draft rounds 1 to 4+, and one category for the Preseason Draft). Due to the limited sample size of players drafted after round five of the national draft, after round four of the rookie draft, and in total from the preseason draft, data were combined into one category for each draft type. Positional role classification was expressed across the seven levels as determined by Champion Data (general defender, key defender, general forward, key forward, midfielder, midfield-forward, and ruck).

Further, as part of the entry concessions given to newly established clubs, the Gold Coast Suns and the Greater Western Sydney Giants, 45 players from the dataset were drafted to AFL clubs prior to the 2011, 2012, and 2013 AFL seasons via non- traditional draft methods. Considering the circumstances of these concessions, all players drafted via methods of zone selection, as an underage recruit, through the AFL mini-draft, as an AFL initiative or were pre-listed by an AFL club (n = 42), were considered as first round selections within the national draft. Further, those drafted after being overlooked in the prior year's national draft (n = 3) were considered as first round selections within the rookie draft.

5.3.3 Statistical analysis

Descriptive statistics for age and experience, and how they relate to AFL Player Ratings [mean ± 95% confidence intervals (CI)] were obtained. The number of matches played per season and proportion of players were also collected and plotted across age and experience. Prior to undertaking the main analyses, Spearman's correlation analyses were employed to determine the extent of collinearity between each of the four player characteristics. This analysis was undertaken using the *Hmisc* package (Harrell Jr, 2017) in the R statistical computing software version 3.3.2. (R Core Team, 2016). This analysis revealed a strong association between age and experience ($r = 0.83$), whilst all remaining associations were weak ($r < 0.15$). As a result, separate models were created throughout the further analyses, utilising age and experience as the independent variables in each.

To determine the extent to which these characteristics affect performance, linear mixed models were applied using the *lme4* package (Bates, Mächler, Bolker & Walker, 2015). Two separate models were created, each incorporating either age or experience, with all other factors included in both. This particular approach was used to control the variability created by the repeated measures data on each player. Specifically, the factors of interest (age, experience, positional role, and draft selection) were treated as fixed effects, and player as a random effect in both models. Each model took the form of:

$$PR_{ps} = \beta_0 + \beta_1 X_{ps} + \beta_2 Y_{ps} + \beta_3 Z_p + \propto_p + \varepsilon_{ps}$$

where PR_{ps} is the AFL Player Rating average of player *p* in season *s* (s = 2013–2017). β_0, β_1, β_2, and β_3 are fixed coefficients, and X, Y, and Z are observed covariates. In model (1), X_{ps} and Y_{ps} represent the player's age and positional role for the corresponding season, respectively, whilst Z_p represents the category outlining the player's draft selection, which stays consistent between seasons. The parameter $\propto_p$ is a player random effect, which makes the intercept of the model specific to each player and allows for individualised performance projections. The player random effect is treated as constant across seasons and each effect is a draw from a normal distribution with equal variance for all players. The parameter ε_{ps} denotes the player season residual error. Model (2) takes the exact same form as model (1), however, X_{ps} instead represents a player's experience for the corresponding season.

Based on the fixed effects estimates, benchmark levels of performance were plotted ($\propto_p = 0$) for age and experience, respectively, where means and 90% prediction intervals (PI) are averaged over the levels of positional role and draft for both. A post hoc Tukey test was performed to adjust for multiple comparisons, and to determine whether performance was different within each level of age and experience, and thus identifying a hypothesised breakpoint in performance. To further assess whether a breakpoint exists in each of the linear mixed models, a segmented model (or "piecewise linear model") was fit to the data to estimate if a change in the trend of the data occurs. This analysis was undertaken using the *segmented* package (Muggeo, 2008). As a result of the *post hoc* Tukey tests, we specified the levels 22 for age, and 41–60 for experience as the hypothesised break points. Within this analysis, these points are used as starting points for which the model uses to estimate breakpoints. A level of significance was accepted at $p < 0.01$ in all analyses.

5.4 Results

Descriptive statistics are outlined in Figures 5.1 and 5.2 for age and experience, and positional role and draft, respectively. Figure 5.3A highlights that the proportion of players competing in the AFL is at its highest at ages 20–22, and then declines with each consecutive age level thereafter. Further, Figure 5.3B highlights that the proportion of players is highest in the least experienced group (20 matches or less), and similarly declines with each consecutive category level of experience thereafter. On the contrary, Figure 5.4 indicates that the average number of matches played per season increases with both age and experience.

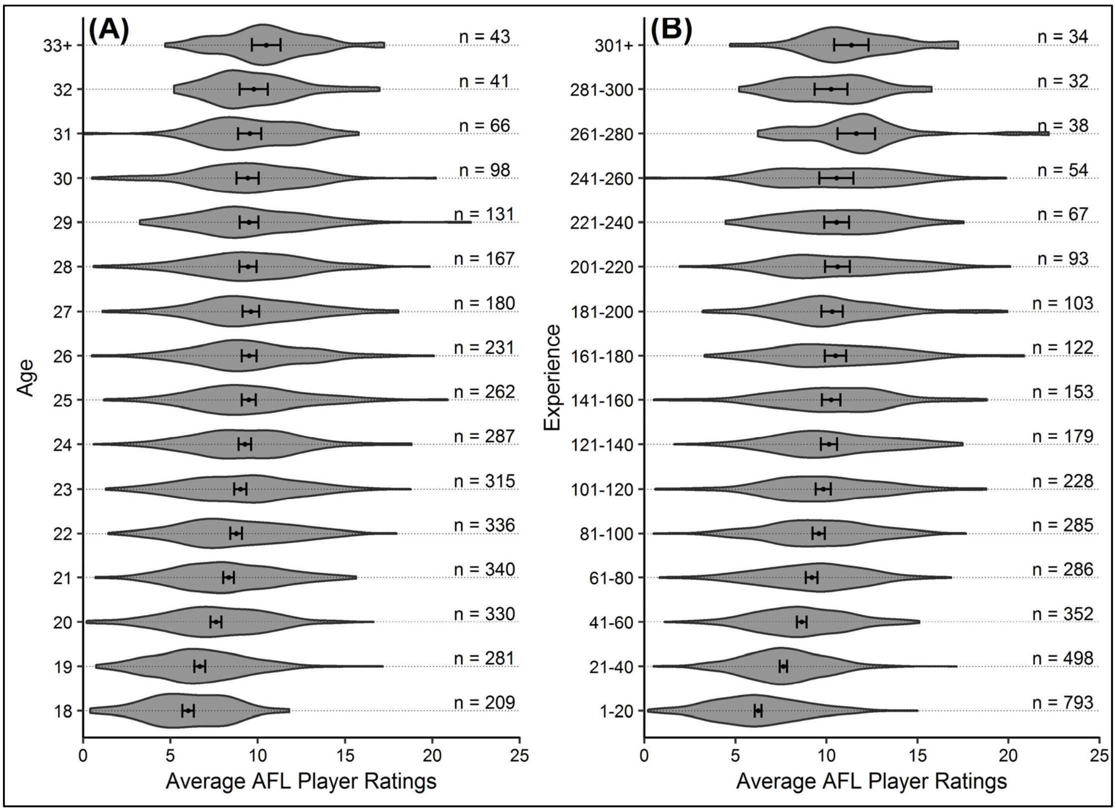

Figure 5.1 **Violin plot outlining the density of the average AFL Player Ratings (± 95% CI) for (A) Age and (B) Experience, respectively. The number of observations in each group are outlined.**

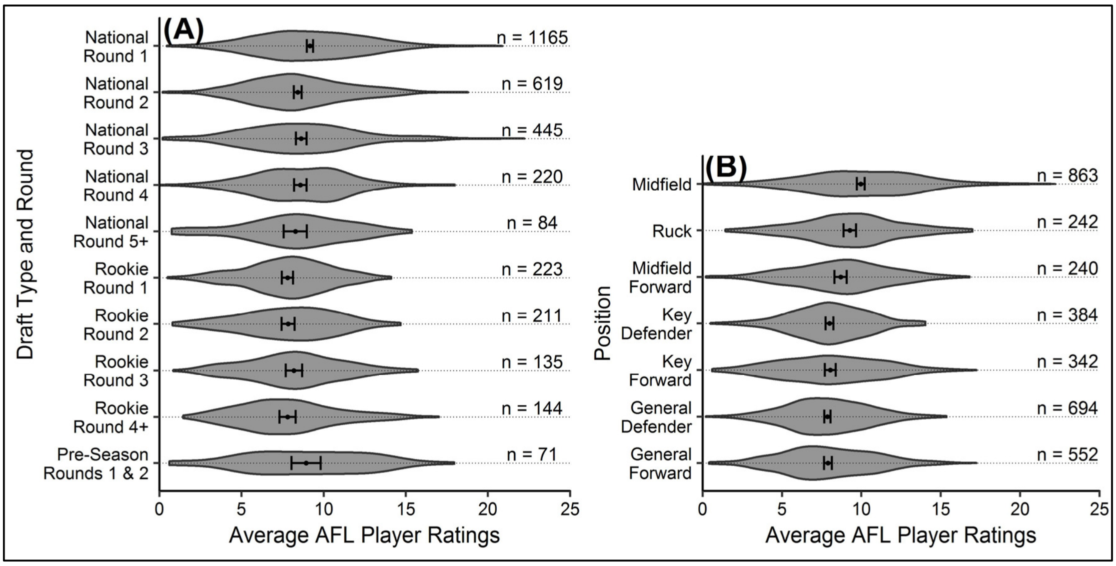

Figure 5.2 **Violin plot outlining the density of the average AFL Player Ratings (± 95% CI) for (A) Draft and (B) Position, respectively. The number of observations in each group are outlined.**

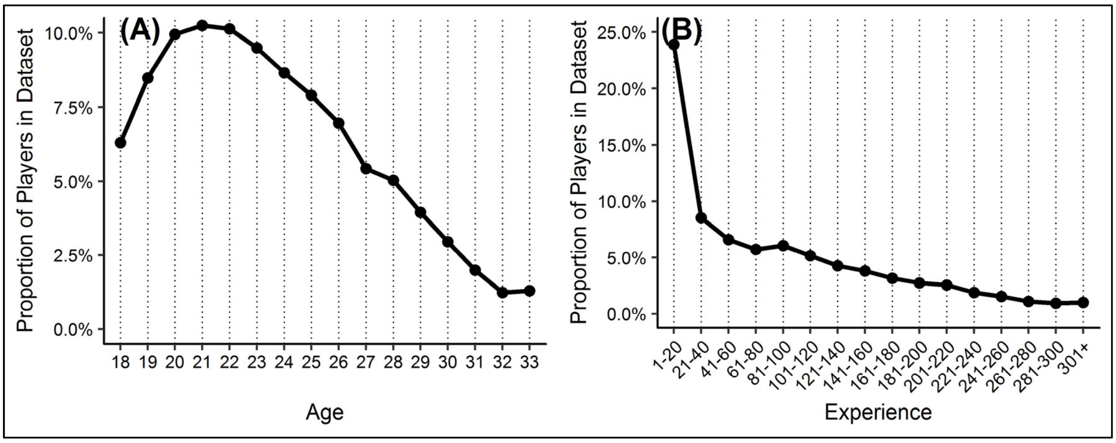

Figure 5.3 **Proportion of players in the dataset by (A) Age and (B) Experience.**

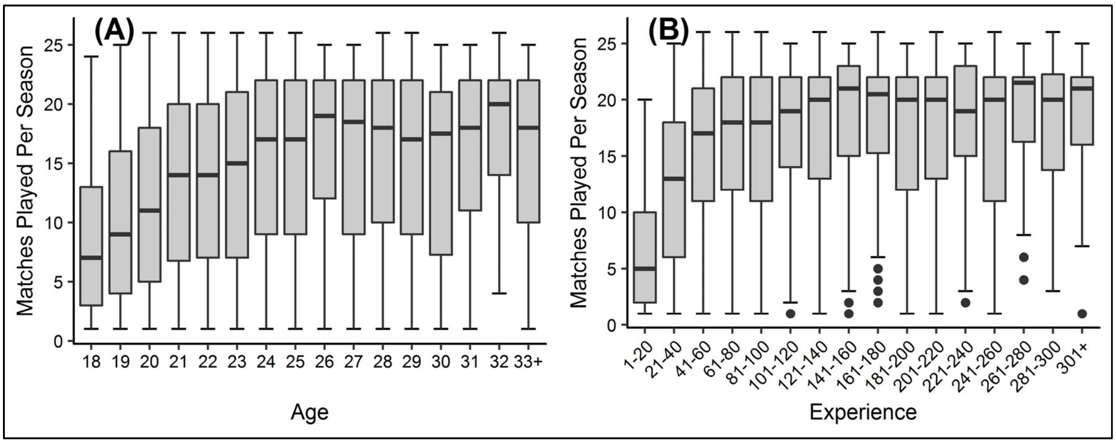

Figure 5.4 Boxplot outlining the proportion of matches played per season by players in each level of (A) Age and (B) Experience.

Results of the linear mixed models revealed that all factors affected levels of performance in both models at $p < 0.01$. Model (1) produced a root mean square error of 1.77 and Chi-square values of 356.9 for age, 98.7 for positional role and 57.1 for draft. Comparatively, model (2) produced a root mean square error of 1.82 rating points and Chi-square values of 523.5 for experience, 100.4 for positional role and 21.7 for draft. The values indicate that age and experience had the largest influence on performance in each of the models, respectively, followed by positional role. Tables 5.1 and 5.2 outline the fixed effect coefficients (β_0, β_1, β_2, and β_3) for each factor level of the characteristics in each of the respective models.

Table 5.1 Model (1) fixed effect regression coefficients outlining the estimated difference in rating points from the reference level of each factor.

	Regression coefficients (± SE)
(Intercept)	7.11 (0.23)
Age 19	0.98 (0.20)
Age 20	1.93 (0.21)
Age 21	2.62 (0.21)
Age 22	3.06 (0.22)
Age 23	3.32 (0.22)
Age 24	3.39 (0.23)
Age 25	3.69 (0.24)
Age 26	3.70 (0.25)
Age 27	3.68 (0.26)
Age 28	3.31 (0.27)
Age 29	3.18 (0.29)
Age 30	2.80 (0.32)
Age 31	2.48 (0.37)
Age 32	2.56 (0.44)
Age 33+	2.46 (0.47)
Positional role Gen Def	-1.25 (0.17
Positional role Gen Fwd	-1.13 (0.17)
Positional role Key Def	-1.128 (0.23)
Positional role Key Fwd	-1.79 (0.23)
Positional role Mid Fwd	-0.79 (0.19)
Positional role Ruck	-0.38 (0.29)
Draft National 2	-0.78 (0.23)
Draft National 3	-0.74 (0.25)
Draft National 4	-0.94 (0.32)
Draft National 5+	-1.21 (0.47)
Draft Rookie 1	-1.47 (0.32)
Draft Rookie 2	-1.62 (0.33)
Draft Rookie 3	-1.56 (0.39)
Draft Rookie 4 +	-1.75 (0.38)
Draft Preseason	-1.03 (0.57)

Reference level for each factor were: Age 18, Positional role Midfield, Draft National 1.

Table 5.2 Model (2) fixed effect regression coefficients, outlining the estimated difference in rating points from the reference level of each factor.

	Regression coefficients (± SE)
(Intercept)	7.43 (0.18)
Experience 21-40	1.31 (0.14)
Experience 41-60	2.32 (0.16)
Experience 61-80	2.79 (0.18)
Experience 81-100	3.19 (0.18)
Experience 101-120	3.38 (0.20)
Experience 121-140	3.48 (0.22)
Experience 141-160	3.39 (0.23)
Experience 161-180	3.77 (0.25)
Experience 181-200	3.43 (0.27)
Experience 201-220	3.53 (0.29)
Experience 221-240	3.32 (0.33)
Experience 241-260	3.02 (0.36
Experience 261-280	3.74 (0.43)
Experience 281-300	2.46 (0.47)
Experience 301+	3.02 (0.52)
Position Gen Def	-1.17 (0.16)
Position Gen Fwd	-1.24 (0.16)
Position Key Def	-1.07 (0.21)
Position Key Fwd	-1.49 (0.22)
Position Mid Fwd	-0.74 (0.19)
Position Ruck	-0.12 (0.26)
Draft National 2	-0.54 (0.20)
Draft National 3	-0.30 (0.23)
Draft National 4	-0.27 (0.29)
Draft National 5+	-0.75 (0.42)
Draft Rookie 1	-0.89 (0.29)
Draft Rookie 2	-0.85 (0.30)
Draft Rookie 3	-0.46 (0.35)
Draft Rookie 4 +	-0.71 (0.34)
Draft Preseason	-0.49 (0.51)

Reference level for each factor were: Experience 1-20, Positional role Midfield, Draft National 1.

Results of the post hoc Tukey test indicated that performance was affected by age at various age levels up until the age of 21 (mean differences ranged from 0.98 to 3.70 player rating points). However, no two levels above the age of 21 were seen to exhibit different levels of performance. For experience, differences were seen at the levels of 1–20 matches and 21–40 matches in comparison to all higher levels of experience (mean differences ranged from 1.01 to 3.77 player rating points), and for various experience levels in comparison to 41–60 matches. No differences were seen between any levels above this for experience.

The segmented models identified a breakpoint in performance for both age and experience. The results indicate that a breakpoint in age occurs between the age levels 22 and 23, where performance is seen to increase linearly 0.75 rating points per age level prior to this breakpoint, and decline linearly 0.09 rating points per age level thereafter. The breakpoint identified for experience occurs between the levels 41–60 and 61–80, where performance is seen to increase linearly 1.24 rating points per level of experience prior to this breakpoint, and then continue to increase linearly 0.04 rating points per experience level thereafter. Figure 5.5 displays the benchmark levels of performance for both age and experience, where player specific random effects (PSRE) are removed. X-axis intercept lines and regression lines were added to Figure 5.5 to represent the level at which the identified breakpoint in performance occurs, and the change in the trend of player performance, respectively, for both age and experience.

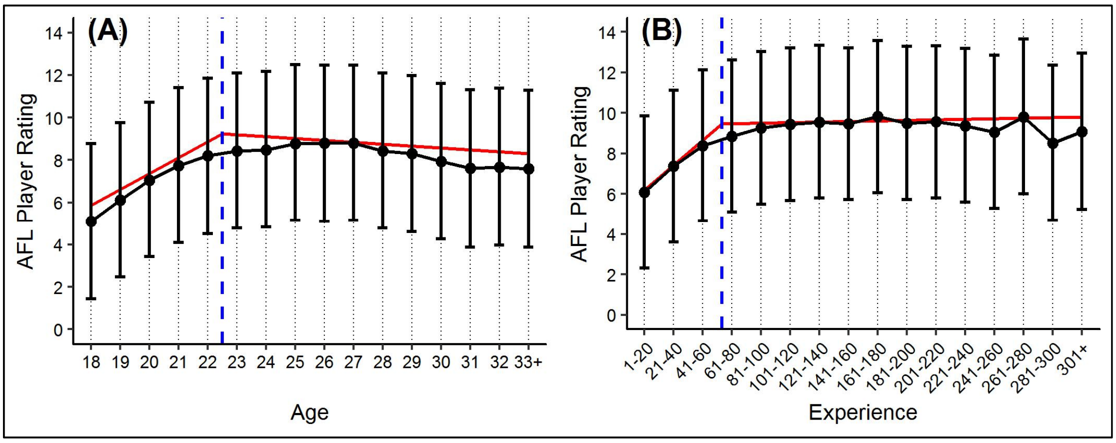

Figure 5.5 Benchmark levels of AFL Player Ratings (± 90% PI) by (A) Age and (B) Experience, based on the fixed effects estimates. Blue x-axis intercept lines represent the level at which the breakpoint in performance occurs for both age and experience, respectively. Red regression lines represent the multiple linear fits of the segmented models.

By applying the PSRE and the fixed effect estimates from the linear mixed models, various applications can be created to benchmark player performance. For example, Figure 5.6 visualises the actual past performance and future player specific expectation of performance (fit and 90% PI) for a specific player, as compared to their fixed effect estimate of performance using model (1). This application indicates the player's performance has been below the benchmark level of performance since 2014, but within the 90% PI, and is expected to remain fairly consistent in the three forecasted seasons. Figure 5.7 outlines how model (1) could be used for player comparison, indicating that the player in blue is likely to perform better in each of the forecasted seasons. Further, Figure 5.8 visualises the actual past performance and future player specific expectation of performance (fit only) for a specific player, using both the models based on age (blue) and experience (red).

Additionally, the PSRE provide a measure of player ranking, which adjusts for the individual fixed effects characteristics. Table 5.3 outlines the top five players in each positional roles, as determined by the average of the PSRE across the two linear mixed models. Player positional role was determined by the category in which they were categorised the most frequently over the five seasons.

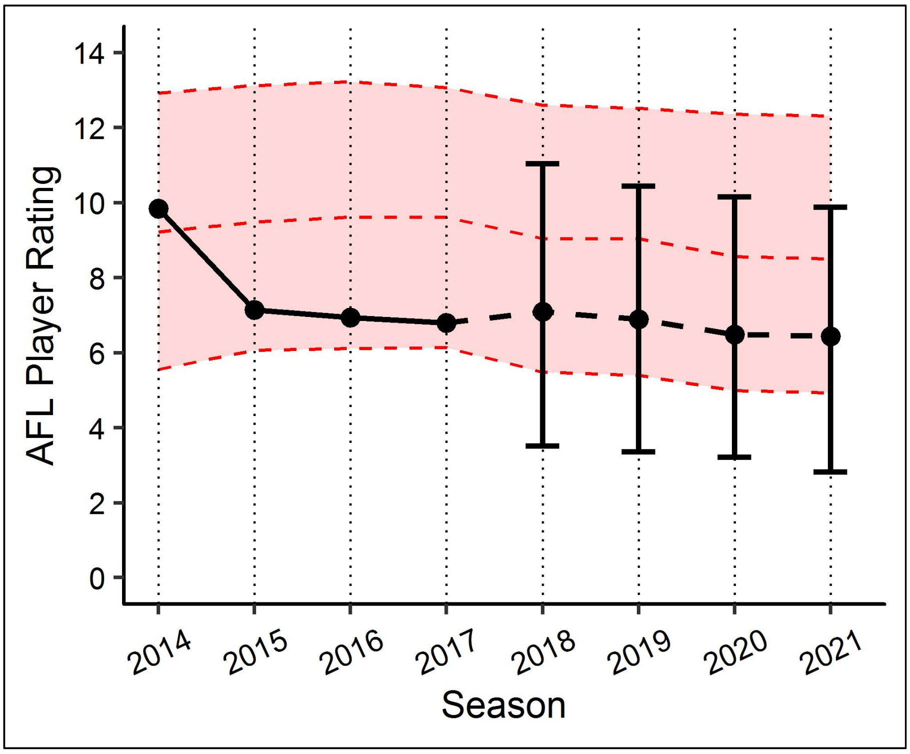

Figure 5.6 **Benchmark levels of AFL Player Ratings for a specific player using the age linear mixed model. Black lines represents actual performance to 2017 & player specific expectation (± 90% PI) of performance from 2018. Red ribbon represents fixed effects estimates based on characteristics of same player.**

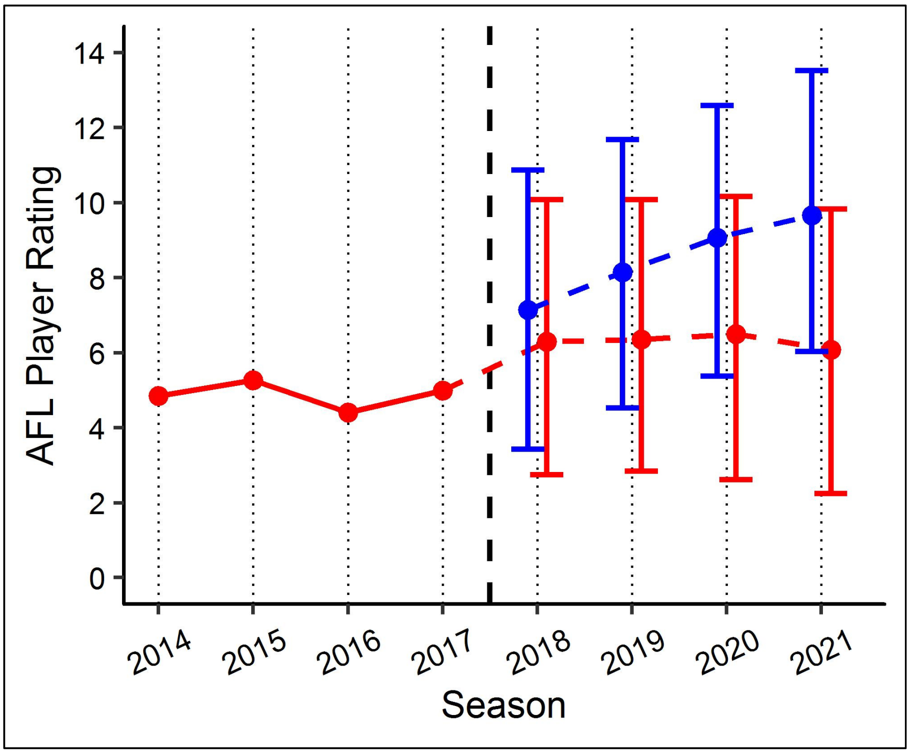

Figure 5.7 **Benchmark levels of AFL Player Ratings for two specific players using the age linear mixed model. Red line represents actual performance prior to 2017. Red and blue lines indicate player specific expectations (± 90% PI) of performance from 2018 for each player. Black x-axis intercept line indicates point of comparison.**

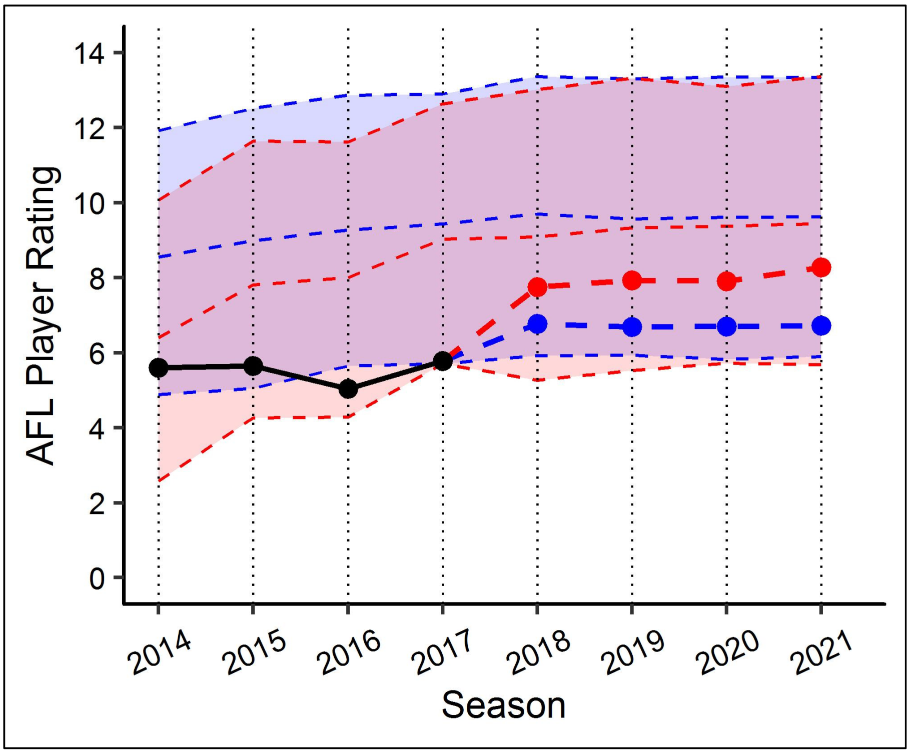

Figure 5.8 **Benchmark levels of AFL Player Ratings for a specific player using the both the age (blue) and experience (red) linear mixed models. Black line represents actual performance to 2017. Blue and red points indicate expectation of performance from 2018 using each the age and experience models, respectively. Similarly, each ribbon represents fixed effects estimates based on characteristics of same player in each model.**

Table 5.3 Top five players in each positional role, as determined by the average of the player specific random effects (PSRE) in each of the linear mixed models. Player positional role determined by the category in which they were categorised the most frequently over the five seasons.

General Defender			**General Forward**		
Player	**Model 1 PSRE**	**Model 2 PSRE**	**Player**	**Model 1 PSRE**	**Model 2 PSRE**
Zac Williams	4.09	3.14	Brent Harvey	6.18	4.74
Adam Saad	3.30	3.22	Chad Wingard	4.31	3.26
Shaun Burgoyne	3.68	2.84	Eddie Betts	4.19	3.19
Brandon White	3.04	2.57	Luke Breust	4.32	3.02
Daniel Rich	2.97	2.57	Cyril Rioli	3.43	3.00
Key Defender			**Key Forward**		
Player	**Model 1 PSRE**	**Model 2 PSRE**	**Player**	**Model 1 PSRE**	**Model 2 PSRE**
Jeremy McGovern	4.44	4.11	Lance Franklin	5.21	4.51
Alex Rance	3.59	2.99	Jarryd Roughead	4.23	3.66
Tom McDonald	2.87	2.16	Justin Westhoff	4.22	3.10
Harris Andrews	3.04	1.87	Josh J. Kennedy	3.73	3.02
Josh Gibson	2.94	1.51	Jack Gunston	3.68	2.99
Midfielder			**Midfield-Forward**		
Player	**Model 1 PSRE**	**Model 2 PSRE**	**Player**	**Model 1 PSRE**	**Model 2 PSRE**
Gary Ablett	8.29	6.96	Robbie Gray	4.75	3.76
Patrick Dangerfield	6.96	6.30	Dayne Zorko	3.71	3.88
Nat Fyfe	6.61	5.77	Sam Menegola	3.30	4.11
Scott Pendlebury	6.09	5.60	Christian Petracca	3.53	3.42
Marcus Bontempelli	5.44	4.49	Luke Dahlhaus	3.82	2.72
Ruck					
Player	**Model 1 PSRE**	**Model 2 PSRE**			
Todd Goldstein	4.70	3.68			
Nic Naitanui	4.29	3.57			
Sam Jacobs	3.60	2.19			
Aaron Sandilands	3.95	1.83			
Shane Mumford	3.52	1.94			

5.5 Discussion

The primary aim of this study was to develop a model to objectively benchmark player performance whilst considering their age, experience, positional role, and both draft type and round in which they were selected. It also aimed to identify the stage of peak performance and specific breakpoints in player performance longitudinally. Separate linear mixed model analyses were implemented to benchmark performance based on the multifactorial fixed effects estimates. Segmented models were fit to these fixed effect estimates to determine if and where a change in the linear trend of performance progression occurs.

Visual inspection of the descriptive statistics in Figures 5.1A and 5.1B indicate that performance continues to improve throughout an AFL players career (as indicated by the gradual increase in average AFL Player Ratings for both age and experience, respectively). However, it must be noted that this type of analysis is susceptible to selection biases (Brander, Egan & Yeung, 2014). Specifically, previous research has identified that these biases can be bought upon as a result of better-performing players typically having longer careers than other players (Bradbury, 2009; Dendir, 2016). Figures 5.3 and 5.4 highlight this bias on the basis that player selection is a subjective identification of each clubs best performers. Specifically, Figure 5.3 outlines the proportion of players in the dataset, and indicates that there are less players across the sample in older and more experienced categories, respectively; however, Figure 5.4 shows that these older and more experienced players on average play more games per season. The substantially smaller interquartile ranges and presence of outliers in Figure 5.4B, as opposed to Figure 5.4A, indicates that despite showing similar increasing trends between the two distributions, there is less variance in matches played per season with respect to experience. However, this is somewhat expected due to the compounding nature of matches played per season, to total career matches. Visual inspection of the descriptive statistics in Figures 5.2A and 5.2B also indicates that performance differences are seen between varying levels of both draft and position, respectively. These findings align with previous literature investigating longitudinal player performance, and supports the use of a mixed model approach to account for fixed and PSRE (Bradbury, 2009; Dendir, 2016).

Each of the two linear mixed models provide context when looking to benchmark player performance longitudinally in AF. In addition to identifying a universal benchmark trend of performance longitudinally, the models produced in this study allow player specific values to be obtained, by adjusting each of the fixed effects relative to the player's characteristics in each model. These player specific benchmarks allow for both retrospective assessment of a players past performance against expected performance, as well as to forecast player performance relative to expected characteristics (assumptions must be made with regards to positional role and experience to forecast). Applications of these models have the potential to be beneficial in supporting the decision-making processes within professional AF organisations. Decisions relating to player recruitment and contracting could be objectively informed by gaining an understanding of the past and future potential performance of players, which the club maybe looking to recruit, resign or remove from their current playing squad. Though the examples provided in this study feature 90% PI, clubs/organisations wanting to be more aggressive with their predictions regarding expected performance could adapt the current models to include lower PI. Figure 5.6 provides a specific example of how this can be visualised. It outlines an actual player's past performance (2014–2017) and expected future performance (2018–2021), and compares this to the benchmark level of performance based on the characteristics for that player. Alternatively, Figure 5.7 outlines an actual player's past performance (2014–2017) and expected future performance (2018–2021), and compares this to the expected future performance (2018–2021) of a player who is yet to be drafted.

Though the identified breakpoints found in each model differ marginally to the findings of the *post hoc* Tukey test, both analyses indicate that there is a distinct change in the trend of player performance occurring in each model, occurring at around the age 22, and experience level 41–60, respectively. Specifically, they indicate that this change in the trend represents a point of marginal gains within each of the model, such that once these levels are reached the benchmark level of player performance is expected to somewhat plateau. This indication of marginal performance gains beyond these respective levels could have useful implications for both player development and player recruiting/contracting within professional AF. For example, clubs may look to persist with selection of players who are yet to reach these points of marginal gains (as opposed to older/more experienced players of similar ability), knowing that match opportunities are potentially more detrimental to development of the younger/less experienced players. In regards to player recruiting and contracting, clubs could look to use these breakpoints as an indication of whether the performance of current players and/or potential recruits is likely to continue to improve, or whether their performance has reached a point of marginal gains. Though only one breakpoint was identified for each model in this study, clubs/organisations wanting to further explore the longitudinal performance trends could adapt the current methodology to identify whether multiple breakpoints exist.

Despite minor differences, both the models measured longitudinally on each age and experience might be used for different operational purposes based on the preferences of the organisation. For example, due to the reliance of match opportunity for the model based experience, applications of this model may be more suited to benchmark the performance of players who have experienced long-term injuries or are mature aged recruits. Conversely, for those who have had sufficient match opportunities, the models based on age may be more suitable due to the more progressive nature of age as an independent variable. Figure 5.8 visualises this difference in the models through benchmarking the expected performance of a specific older age, but lowly experienced individual, using both models.

In addition to providing benchmark levels of performance, the models produced in this study also provide an indication of the point at which peak performance occurs longitudinally. Specifically, the findings imply that on average players reach their peak around the age of 22, or 60 matches experience. In comparison to previous literature, this point at which the average player reaches their peak age is younger than what has been identified in other dynamic team sports such as soccer (Dendir, 2016). Though this peak is identified earlier, there was no substantial drop-off in performance noted in this study, indicating that that peak performance in AF may be better outlined by a peak range. There is no literature available to make these comparisons in relation to a player's match experience.

The PSRE outlined in each of the mixed models could also be used to rank players across the 2013–2017 seasons. Specifically, this type of ranking would be more generalisable than other ranking measures that do not adjust for fixed effects such as those used in our model. Thus it allows comparisons to be made between players across different ages, levels of experience, positional roles and draft selections. Table 5.3 outlined the top five players in each positional role. The table indicated that despite accounting for position, the top three midfielders still exhibited higher PSRE than any other players. As an indication of the face validity for these random effects to be used to rank players, each of these three outlined individuals have won the AFL's award for the fairest and best player for one of the five seasons included in the dataset (Gary Ablett in 2013, Nat Fyfe in 2015 and Patrick Dangerfield in 2016).

Some limitations of this study should also be noted. Though mixed model approaches have been supported in previous literature to account for the fixed and random effects associated with longitudinal player performance; there is also an inherent understanding that the decline in performance after peak is often underestimated as a result of athlete drop out. For example, only the most successful athletes continue to get renewed playing contracts, and are subsequently selected to play at the elite level. Thus meaning that there is likely some level of performance deterioration that goes unnoticed by the model beyond certain ages/levels of experience. Another limitation is that the methodology could include additional metrics, such as time on ground or spatiotemporal data, potentially allowing for further explanation of the results. Future work in dynamic team sports should focus on the continual development of improving objective player performance rating models, as well as decision support applications to assist with operational decision-making in professional sporting organisations. In AF specifically, the development of these objective player performance rating models could look to include further positioning dynamics, similar to that in other team sports (Gonçalves et al., 2017; Memmert et al., 2017).

5.6 Conclusion

This study produced two types of models benchmarking player performance in the AFL. The first method utilised two separate linear mixed models to identify the effect of individual characteristics on player performance. Each of these models could be used to identify how a player’s performance compares to individualised benchmarks, or to forecast future potential performance. The second method utilised segmented models, finding a point of marginal gains within longitudinal performance of both age and experience. The implementation of these methodologies may provide valuable knowledge for professional AFL organisations. Implications of their use could assist with organisational decisions relating to player recruitment, contracting and development. Future work should focus on the refinement of the models produced in this study as additional seasons of data become available.

CHAPTER SIX – STUDY IV

Chapter Overview

Chapter Six is the fourth and final study contained in this thesis. The study looks to identify the relationship between subjective ratings of performance and basic player performance indicators, in order to gain an understanding of the extent to which human decisions are related to measurable aspects of a player's performance. It also looks to compare subjective and objective ratings of player performance. The methodologies are expressed as an exemplar of what could be implemented within professional sporting organisations using their own specific subjective rating processes.

This chapter contains an abstract (section 6.1), introduction (section 6.2), methods (section 6.3), results (section 6.4), discussion (section 6.5) and conclusion (section 6.6) sections. The content of this chapter was published in PLOS ONE (McIntosh, Kovalchik & Robertson, 2019a). Additionally, preliminary work relating to the study was presented at the 9th World Congress on Science and Football.

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RESEARCH ARTICLE

Comparing subjective and objective evaluations of player performance in Australian Rules football

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Abstract

Player evaluation plays a fundamental role in the decision-making processes of professional sporting organisations. In the Australian Football League, both subjective and objective evaluations of player match performance are commonplace. This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance. A secondary aim was to compare subjective and objective ratings of player performance. Inside Football Player Ratings (IFPR) and Australian Football League Player Ratings were collected as subjective and objective evaluations of player performance, respectively, for each player during all 1026 matches throughout the 2013–2017 Australian Football League seasons. Nine common player performance indicators, player role classification, player age and match outcomes were also collected. Standardised linear mixed model and recursive partitioning and regression tree models were undertaken across the whole dataset, as well as separately for each of the seven player roles. The mixed model analysis produced a model associating the performance indicators with IFPR at a root mean square error of 0.98. Random effects accounting for differences between seasons and players ranged by 0.09 and 1.73 IFPR each across the five seasons and 1052 players, respectively. The recursive partitioning and regression tree model explained IFPR exactly in 35.8% of instances, and to within 1.0 IFPR point in 81.0% of instances. When analysed separately by player role, exact explanation varied from 25.2% to 41.7%, and within 1.0 IFPR point from 70.3% to 88.6%. Overall, kicks and handballs were most associated with the IFPR. This study highlights that a select few features account for a majority of the variance when explaining subjective ratings of player performance, and that these vary by player role. Australian Football League organisations should utilise both subjective and objective assessments of performance to gain a better understanding of the differences associated with subjective performance assessment.

Introduction

Player evaluation plays a fundamental role in the decision-making processes of professional sporting organisations, including player monitoring, team selection, player contracting and

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scouting [1–3]. Despite widespread and available objective data within professional team sports, a reluctance of key decision makers to utilise these measures to develop and integrate decision support systems within their organisations remains [4–6]. Despite this reluctance, there has been various literature outlining the benefits of considering objective evaluations of performance to support organisational decision-making processes [3, 7, 8]. Though these studies proclaim the benefits of objective evaluations (i.e., reliability and consistency), they each emphasise the importance of utilising both objective and subjective evaluations of performance in a complementary manner, to highlight whether inconsistencies exist between the evaluations and to ultimately improve player evaluation.

Australian Rules football (AF) is a dynamic invasion team sport played on a large oval field between two opposing teams consisting of 22 players each (18 on the field and four interchange). Due to the dynamic nature of the sport and the complex interactions which occur in AF, individual performance is difficult to analyse, both subjectively and objectively [9, 10]. Despite this, various objective player performance measures have been created based on player performance in the elite competition of AF, the Australian Football League (AFL). Examples within the notational analysis literature include Stewart, Mitchell [11] who created a player ranking model by identifying the most important performance indicators, and including those with the strongest relationship to team winning margin. Heasman, Dawson [12] created a player impact rating which assigned numerical values to each performance indicator relative to its perceived worth. These values were then weighted relative to environmental situations of the match, and adjusted relative to a players time on ground.

Various objective player performance measures also exist for commercial purposes. Examples include the 'AFL Player Rankings' and the 'AFL Player Ratings', which are both produced by statistics provider Champion Data (Champion Data Pty Ltd., Melbourne, Australia). The former takes a similar approach to that of Stewart, Mitchell [11], however extends this model to include over 50 variables [13], and is used for the fantasy competition 'SuperCoach' (https://supercoach.heraldsun.com.au/). The latter takes an alternate approach to most player performance rating systems, and is based on the principle of field equity. In this system, each action is quantified relative to how much the action increases or decreases their team's expected value of scoring next [14]. A player's overall performance is then measured by the overall change in equity that is created by that player's actions during the game [14].

Subjective analyses of performance are also commonplace within the AFL. Examples include the AFL Coaches Association award and the AFL's award for the fairest and best player (Charles Brownlow Medal). Votes for each of these awards are cast at the conclusion of each match, based on the players deemed most influential during the match. Votes for the AFL Coaches Association award are cast by the senior coaches from both competing teams, and votes for the fairest and best player are cast by the field umpires. Further, various clubs use subjective coach ratings as a way of determining club based awards [15], and various media sources publish subjective ratings for public interest.

A common criticism of player performance evaluation in AF, as well as other team sports (i.e., basketball), is their bias towards players whose specific role involves being more frequently involved in the play, enabling their actions to have a more tangible effect on performance evaluation [16, 17]. These biases have been noted within the notational team sport literature in relation to both subjective and objective player performance analyses [12, 18]. For AF, this specifically relates to midfield players whose role is more centred on following the play to obtain/maintain possession of the ball and improving their team's field position. Previous objective player performance measures have combatted this by suggesting that player performance comparisons should be only made within players who play the same player roles [12]. Similar suggestions have been made in other team sports such as rugby union [18].

Despite frequent studies in the team sport notational analysis literature looking to encourage the use of objective performance rating systems [10, 19, 20], very few studies have looked specifically at identifying the specific mechanisms behind subjective evaluation of individual performance in team sports. Pappalardo, Cintia [8], analysed human evaluations of elite soccer performance using performance indicators and contextual information relating to each match performance. The authors illustrated that subjective ratings of performance were biased towards specific performance indicators, as well as contextual factors such as the outcome of a game, and the expected outcome of a game as estimated by bookmakers. Their findings indicated that in order to improve overall performance evaluations, player analysis should be a balance between objective performance measures and subjective values such as insights from qualitative skill qualities. These findings are indicative of those in other fields, which have shown that humans are susceptible to many errors and biases in decision making, and have limits to the amount of information they can comprehend [21, 22].

In AF, the majority of research on evaluating player performance has had a specific focus on assessing performance indicators in order to explain or predict playing performance [11, 12, 23–26]. Further to this, various other research in AF has been undertaken in other areas, such as assessing the relationship between performance indicators and match outcome [2, 27, 28], playing position [29, 30], and trends in game-play [31].

This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance in the AFL. A secondary aim was to compare subjective and objective ratings of player performance. The rationale for this study was to identify the relationship between subjective ratings of performance and the most basic comprehendible performance indicators, in order to add to the existing understanding of the extent to which human decisions are related to measurable aspects of a player's performance. The methodologies are expressed as an exemplar of what could be implemented within professional AF organisations using their own specific subjective rating processes. An understanding of these insights could be beneficial in supporting organisational decisions relating to weekly team selection, player recruitment, as well as player contracting and financial remuneration; each which have ramifications on team outcomes.

Materials and methods

Data

Two separate measures of player performance were collected for each player during 1026 matches played throughout the 2013–2017 AFL seasons. This included 22 matches played by each team during the regular season, as well as a total of nine matches played throughout the finals series each season. One match was abandoned prior to play during the 2015 season. Further, the eight drawn matches that occurred throughout the 2013–2017 seasons were removed from the analyses.

The Inside Football Player Ratings (IFPR) were obtained from http://www.aflplayerratings.com.au, which is a subjective measure of player performance, rated continuously from zero to ten, based on human interpretation of a player's performance ('Inside Football' is the commercial publication for these publically available player ratings). The ratings for each match were completed by a single AFL accredited journalist who was covering the game for Inside Football (most of whom had 10+ years in the industry). The journalist covering the game was at the ground in the majority of instances, and ratings were provided immediately post-match. The AFL Player Ratings were acquired from Champion Data (also available from http://www.afl.com.au/stats), which is an objective measure of player performance, rated on an open-ended continuous scale, and based on the principle of field equity [14]. The rating process is derived from contextual information collected in real time by trained Champion Data staff (corrected postgame), and is determined by how much each player's actions increase or decrease their team's expected value of scoring [14]. The validity and reliability of the data provided by Champion Data is not publicly available. However, previous research conducted in AF has reported the validity of the performance indicators collected by Champion Data as high [32], and the reliability (as determined by an external assessment) as very high (ICC ranged from 0.947–1.000 for the included performance indicators) [2]. Nine player performance indicators were collected from http://www.afl.com.au/stats, for each player and match included in the dataset. These indicators were selected due to being widely reported and available, as well as being previously reported in the literature [2, 11, 28]. These performance indicators and their definitions are outlined in Table 1. Player role classifications were collected for each player, based on Champions Data's classification for each player at the end of each respective AFL season. These classifications are defined in Table 2. Additionally, a player's age for each corresponding season (range: 18 to 40), and the match outcome for each match (Win and Losses; dummy coded as 1 and 0, respectively) were also collected. See S1 Dataset for all data collected on players.

Statistical analysis

Descriptive statistics (mean and standard deviation) were calculated for each of the two player rating measures, as well as for each respective player role. To determine the variation between the two rating systems, as well as each of the playing roles, the coefficient of variation was calculated for each. To determine the level of association between the two player rating systems and each of the features univariately (all performance indicators, as well as age and match outcome), correlational analyses were undertaken. This analysis was undertaken using the *Hmisc* package [33] in the R statistical computing software version 3.3.2 [34], and visualised using a correlogram.

A linear mixed model analysis was undertaken to determine the extent to which each of the features explained IFPR. This particular approach was used to control the variability created by the repeated measures on each player. This analysis was undertaken using the *lme4* package [35]. All factors (besides position) were standardised and centred with a mean = 0 prior to the

Table 1. Definitions of the Australian rules football performance indicators used in this study.

Performance Indicator	Definition
Kick	Disposing of the football with any part of the leg below the knee.
Handball	Disposing of the football by hitting it with the clenched fist of one hand, while holding it with the other.
Mark	Catching or taking control of the football after it has been kicked by another player a distance of at least 15 metres without touching the ground or being touched by another player.
Tackle	Taking hold of an opposition player in possession of the ball, in order to impede his progress or to force him to dispose of the ball quickly.
Free For	An infringement in favour of the player as called by the umpire.
Free Against	An infringement against the player as called by the umpire.
Hitout	A tap by a ruckman after a ball up or bounce by the umpire.
Goals	The maximum possible score (6 points) achieved by kicking the ball between the two goalposts without touching a post or any player.
Behinds	A score worth one point, achieved by the ball crossing between a goalpost and a behind post, or by the ball hitting a goalpost, or by the ball being touched prior to passing between the goalposts.

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Table 2. Champions data's descriptions of the seven player roles used in this study.

Player Roles	Description
General Defender	Plays a role on opposition small-medium forwards and usually helps create play from the backline
Key Defender	Plays on opposition key forwards with the primary role of nullifying his opponent
General Forward	Plays predominantly in the forward half of the ground but with more freedom than a key forward
Key Forward	Plays predominantly as a tall marking target in the forward line
Midfielder	Spends the majority of time playing on the ball or on the wing
Midfield Forward	Splits time equally between the forward line and the midfield. Often lines up on the half-forward flank but plays a significant amount of time in the midfield
Ruck	Has the primary role of competing for hit-outs at a stoppage

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analysis to allow for Beta coefficient comparisons. In the model, player and season were treated as separate random effects, whilst all other factors were considered as fixed effects.

A recursive partitioning and regression tree model [36, 37] was undertaken as a secondary method to determine the extent to which each of the features explained IFPR. This analysis was undertaken using the *rpart* package, which uses the CART algorithm (classification and regression trees) [38]. A minimum of 100 cases were needed for each node to split, and the complexity parameter was set at 0.001 in order to maximise the number of outcome variables in the model. These measures were employed in order to avoid overfitting and to produce a more parsimonious model. Data were split whereby the 2013–2016 seasons were used to train the model, which was then subsequently tested on the 2017 season. Results of the model were displayed using a tree visualisation and a histogram outlining the model accuracy. Additionally, the recursive partitioning and regression tree analysis was conducted firstly on the whole dataset and then separately for each of the seven respective player roles.

A comparison of the IFPR and AFL Player Ratings was created for two specific players as a practical decision support application. Specifically, the deviation of each player's season mean ratings was compared to the overall sample mean for each rating system. This application allowed for a descriptive analysis and visualisation of the difference in evaluation between the subjective and objective systems.

Results

Descriptive statistics of each player role for both the IFPR and the AFL Player Ratings measures are presented in Fig 1. The overall mean and standard deviation of each rating system was 5.25 ± 1.73 for the IFPR, and 9.65 ± 5.58 for the AFL Player Ratings. The coefficient of variation for each system was 32.9% and 57.8%, respectively. The results of the Pearson's correlation analysis indicated a moderate association ($r = 0.60$) between the AFL Player Ratings and the IFPR. Further, the IFPR and marks both showed moderate associations ($r = 0.64$ and $r = 0.53$) with kicks. All of the remaining associations were $r < 0.50$ and are outlined in Figs 2. and 3 outlines the distribution on AFL Player Ratings along the various levels of IFPR, indicating that as the IFPR increases, the mean AFL Player Ratings increases and the distribution becomes more spread.

The results of the linear mixed model are outlined in Table 3. All features except for frees against, behinds and age contribute significantly to the model ($p < 0.001$), with kicks and handballs having the highest Beta coefficients of 0.844 and 0.646, respectively. The model produced a root mean square error of 0.98 in association with the IFPR. The random effect accounting for the difference between seasons ranged by 0.09 IFPR across the five seasons,

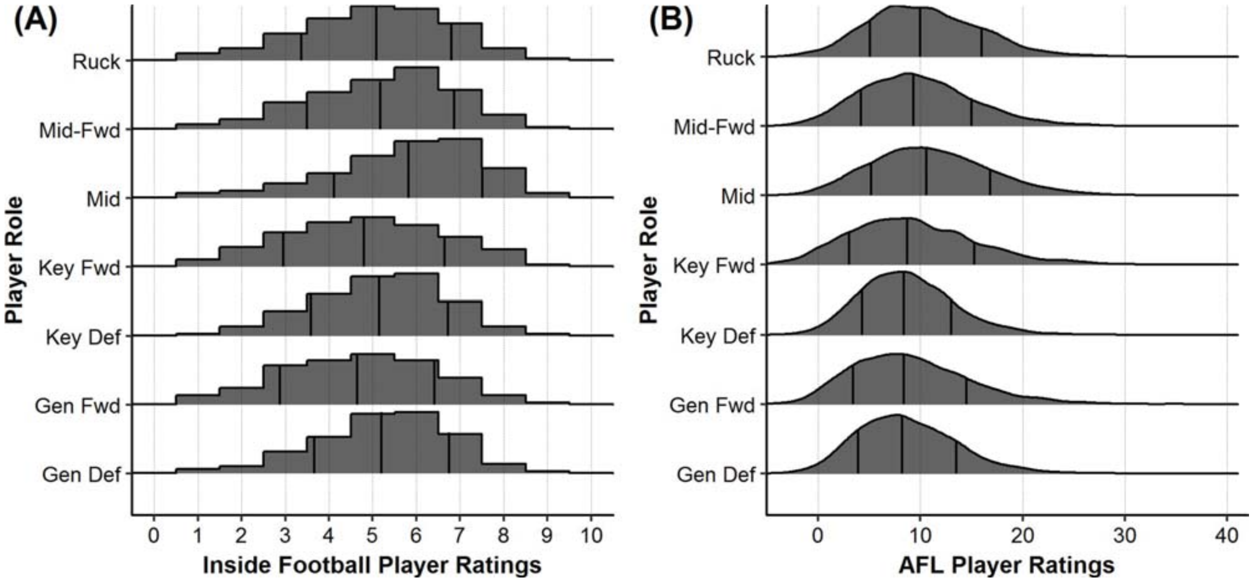

Fig 1. Standardised density distribution (%) of each player role. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013–2017 AFL seasons. Vertical lines indicate mean and ± one standard deviation.

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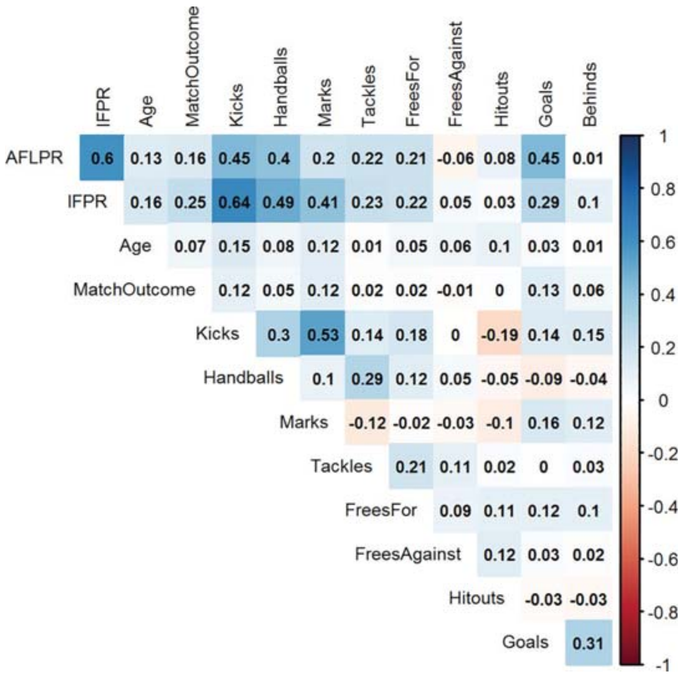

	IFPR	Age	MatchOutcome	Kicks	Handballs	Marks	Tackles	FreesFor	FreesAgainst	Hitouts	Goals	Behinds
AFLPR	0.6	0.13	0.16	0.45	0.4	0.2	0.22	0.21	-0.06	0.08	0.45	0.01
IFPR		0.16	0.25	0.64	0.49	0.41	0.23	0.22	0.05	0.03	0.29	0.1
Age			0.07	0.15	0.08	0.12	0.01	0.05	0.06	0.1	0.03	0.01
MatchOutcome				0.12	0.05	0.12	0.02	0.02	-0.01	0	0.13	0.06
Kicks					0.3	0.53	0.14	0.18	0	-0.19	0.14	0.15
Handballs						0.1	0.29	0.12	0.05	-0.05	-0.09	-0.04
Marks							-0.12	-0.02	-0.03	-0.1	0.16	0.12
Tackles								0.21	0.11	0.02	0	0.03
FreesFor									0.09	0.11	0.12	0.1
FreesAgainst										0.12	0.03	0.02
Hitouts											-0.03	-0.03
Goals												0.31

Fig 2. Correlogram outlining the Pearson correlation coefficients (*r*) between all features used within the study.

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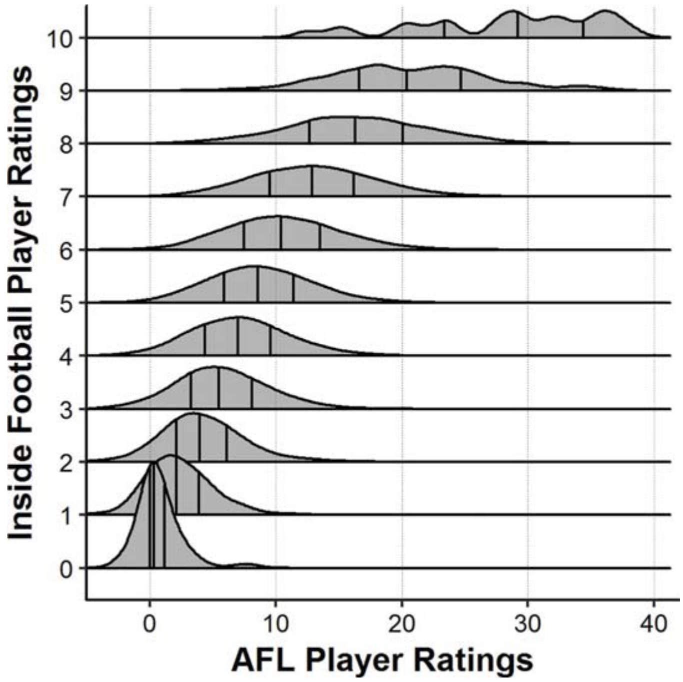

Fig 3. Standardised density distribution (%) of AFL Player Ratings across levels of Inside Football Player Ratings. Vertical lines indicate mean and ± one standard deviation.

https://doi.org/10.1371/journal.pone.0220901.g003

Table 3. Results of the linear mixed model (dependent variable is "Inside Football Player Ratings").

Performance Indicator	β	Std. Error	P
Kicks	0.844	0.007	< 0.001
Handballs	0.646	0.006	< 0.001
Marks	0.091	0.006	< 0.001
Tackles	0.150	0.006	< 0.001
Frees For	0.047	0.005	< 0.001
Frees Against	-0.004	0.005	0.467
Hitouts	0.290	0.011	< 0.001
Goals	0.510	0.006	< 0.001
Behinds	0.004	0.005	0.473
Match Outcome	0.217	0.005	< 0.001
Age	0.011	0.010	0.261
Positional role (General Forward)	-0.406	0.026	< 0.001
Positional role (Key Defender)	0.486	0.030	< 0.001
Positional role (Key Forward)	-0.330	0.035	< 0.001
Positional role (Midfield)	-0.310	0.023	< 0.001
Positional role (Midfield Forward)	-0.310	0.028	< 0.001
Positional role (Ruck)	-0.321	0.054	< 0.001

Reference level for positional role: General Defender.

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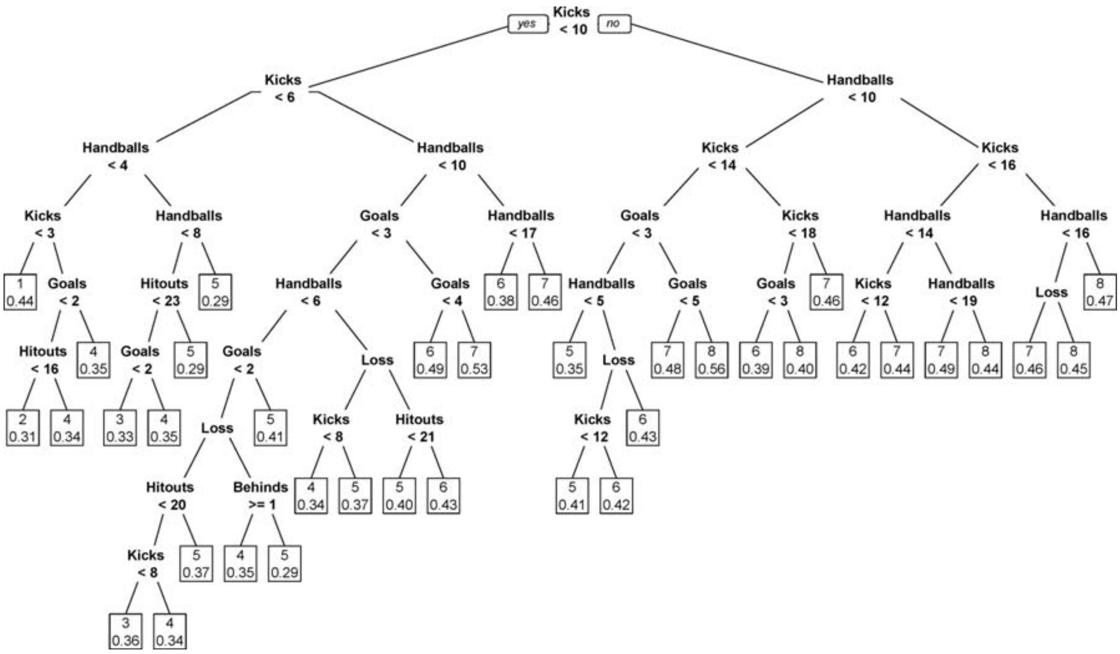

Fig 4. Recursive partitioning and regression tree model explaining Inside Football Player Ratings from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.

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indicating minimal variation. The random effect accounting for differences between players ranged by 1.73 IFPR across the 1052 players, indicating that the mixed model varied substantially in its ability to explain player performance for all players.

The full recursive partitioning and regression tree model is presented in Fig 4. Despite having 38 terminal nodes, only the features relating to ball disposal (kicks and handballs), scoring (goals and behinds), match outcome and hitouts contribute to the model. The splitting of the nodes within each branch indicates that having a greater total count of each performance indicator results in a higher rating of performance, except for behinds. None of the terminal nodes explain the outcome variables zero, nine or ten. The results of this model are outlined in Fig 5 and display that the IFPR could be explained exactly in 35.8% of instances, and within 1.0 IFPR point 81.0% of the time. The positive x-axis variables indicate that the model-expected IFPR was higher than the actual IFPR. Conversely, the negative x-axis variables indicate that the model-expected IFPR was lower than the actual IFPR.

S1–S7 Figs outline the separate recursive partitioning and regression tree models based on each player role. As with the full model, none of the terminal nodes explain the outcome variables zero or ten; however the models based on Key Forwards and Midfielders do explain the outcome variable nine. Further, the model based on Key Defenders also excludes the outcome variables one and eight. Each of the separate models included six or more features, with kicks and handballs featuring heavily in all. Kicks was the root node in all models except for Rucks and Key Forwards, where hitouts and goals where the root node in each, respectively. The most notable additional changes from the full model were that goals featured frequently in the models for Key and General Forwards, marks featured frequently in Key and General Defenders, as well as Key Forwards, tackles for General Defenders, Key Forwards and Midfielders,

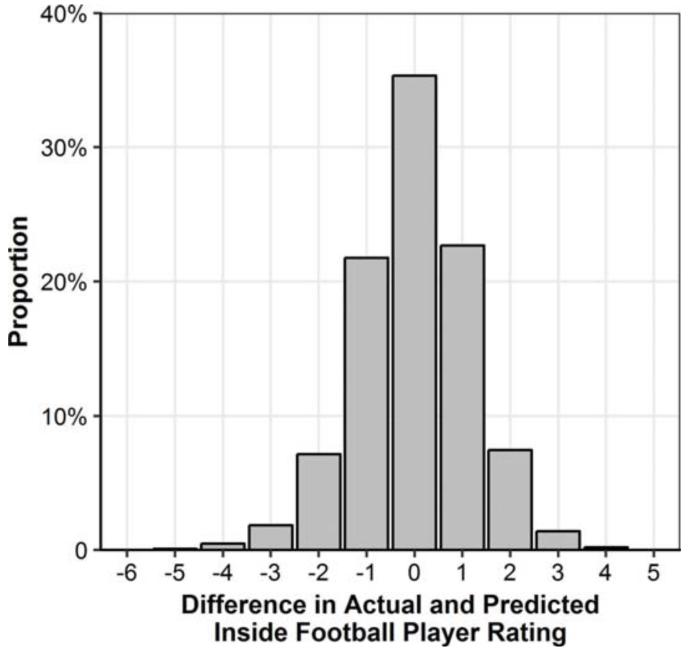

Fig 5. Difference in actual and model-expected Inside Football Player Ratings.

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and hitouts for Ruckmen. The range of accuracy for explaining IFPR exactly in these separate models varied from 25.2% for Key Defenders to 41.7% for Midfielders. The accuracy within 1.0 IFPR point either side varied from 70.3% for Key Defenders to 88.6% for Midfielders.

Fig 6 outlines the distribution of IFPR and AFL Player Ratings for winning and losing teams across the five seasons. The abovementioned random effects accounting for player differences provide an indication of the individual players who were most consistently under- and over-rated as estimated by the linear mixed model, after adjusting for the fixed effect factors. Two individuals were selected, with a comparison of subjective and objective evaluations of their performance undertaken as an exemplar of the application. Specifically, in order to compare their evaluations between the two rating systems on different scales, the deviation of their seasonal mean rating from the overall sample mean were calculated for each system. Table 4 outlines the deviation of their seasonal mean ratings from the overall sample mean of rating values for the two respective players. Additionally, Figs 7 and 8 outline how this could be visualised for ease of interpretability in an applied setting.

Discussion

This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance. A secondary aim was to compare subjective and objective evaluations of player performance. To achieve the primary aim, two separate models were fit identifying the relationship between our exemplar subjective rating system, the IFPR, and the selected performance indicators. To achieve the secondary aim, a descriptive analysis and visualisation was conducted to outline the potential discrepancies noted between subjective and objective evaluations of player performance. Together, these methodologies are expressed as

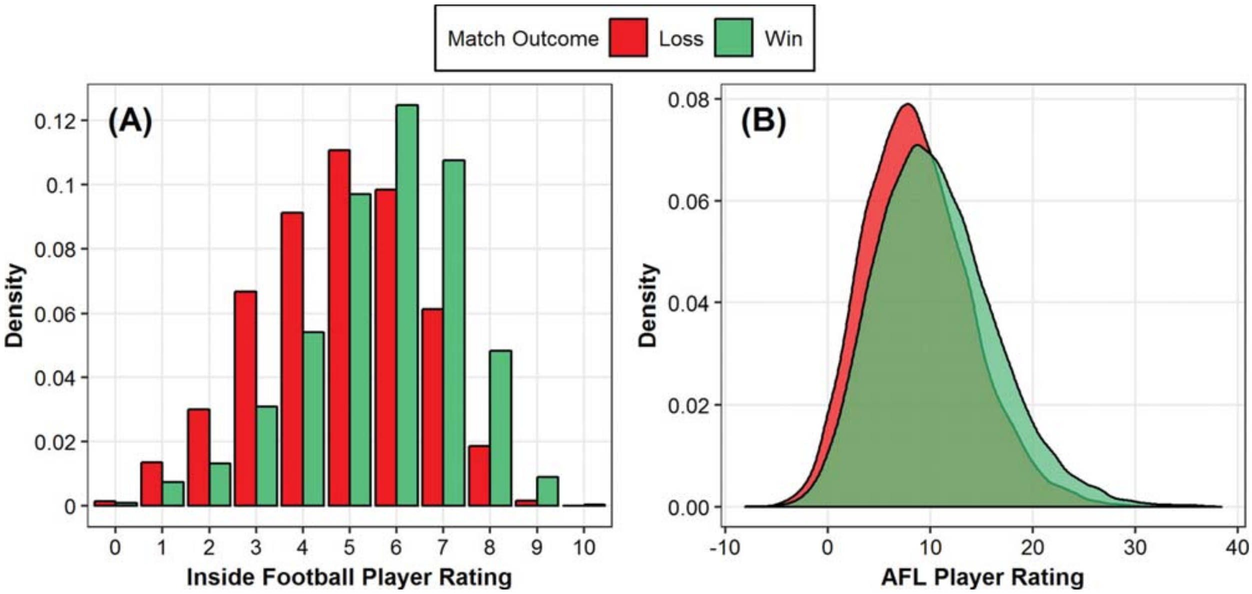

Fig 6. Density of ratings given for all players based on match outcome (Wins and Losses). (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013–2017 AFL seasons.

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an exemplar of what could be implemented within professional AF organisation using their own specific subjective rating processes.

Inspection of the coefficient of variation for each playing role, and the descriptive statistics outlined in Fig 1 indicates that the distribution of ratings in the subjective IFPR system is more variable between each of the player role classifications, in comparison to the objective AFL Player Ratings system. In addition to this, in both ratings systems the mean values for midfielders are higher than that for all other player roles. This aligns with the aforementioned biases noted within both AF and the wider team sport literature [12, 16, 17].

Both the linear mixed model and recursive partitioning and regression tree models provide an objective view of how subjective analyses of performance are explained. Each of the models reflect the results of the other, and outline that when explaining subjective assessment of performance, a small number of features account for a large majority of the variance. The changes seen in the recursive partitioning and regression tree model once analysed separately by position supports the notion that specific indicators differ between playing roles, indicating that controlling for player role when explaining player performance subjectively is important, to

Table 4. Variation of seasonal mean ratings from the overall sample mean ratings for Paul Puopolo and Ben Jacobs.

	Paul Puopolo			Ben Jacobs		
Season	IFPR SD from Sample Mean	AFL Player Rating SD from Sample Mean	Difference in Deviation	IFPR SD from Sample Mean	AFL Player Rating SD from Sample Mean	Difference in Deviation
2013	0.93	0.94	-0.01			
2014	0.37	0.60	-0.23	-0.91	-0.74	-0.17
2015	0.39	0.92	-0.53	-0.15	-0.78	0.63
2016	0.17	0.98	-0.81	0.60	-0.76	1.36
2017	-0.56	0.83	-1.39	1.07	-0.70	1.77

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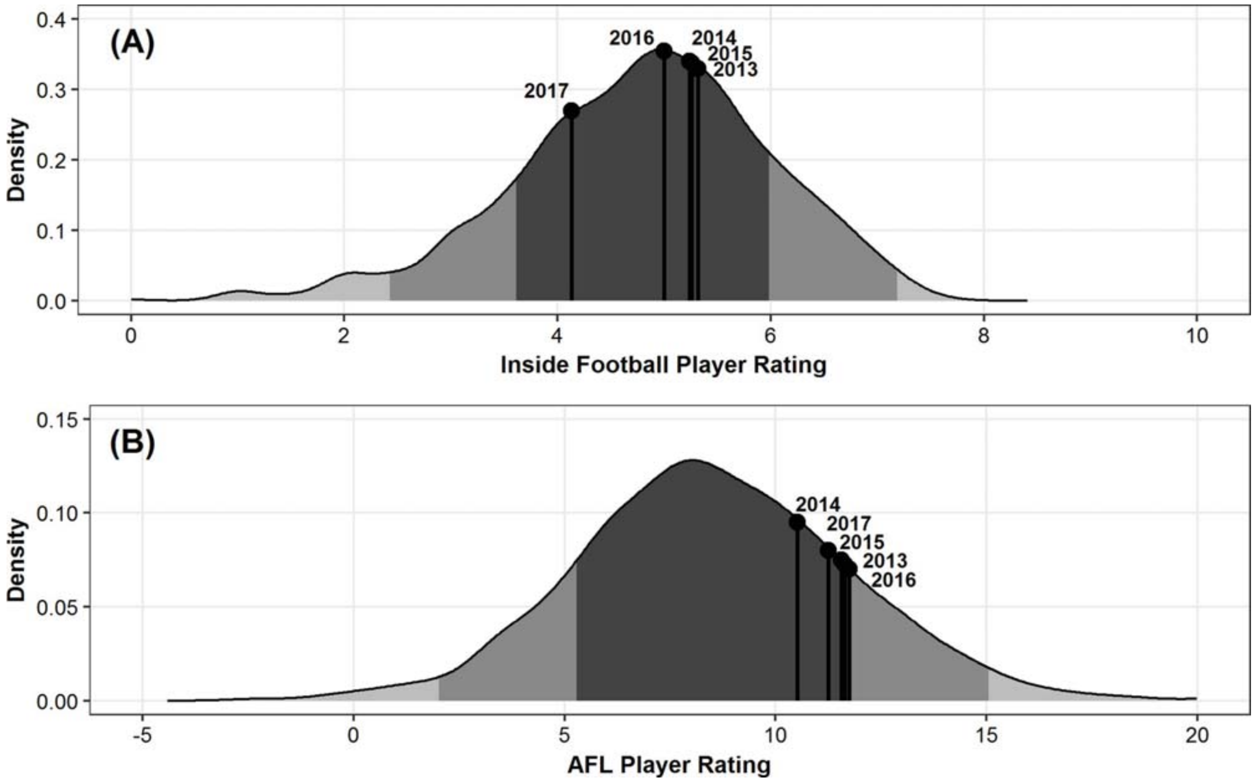

Fig 7. Paul Puopolo's average season ratings in comparison to the distribution of all player's average ratings. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013–2017 AFL seasons. Dark grey indicates mean ± SD, medium grey indicates one to two SD, and light grey indicates two plus SD.

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account for the roles specific to each positional group [39]. Further, both models display a negative association between behinds and expected IFPR, thus indicating that behinds might be viewed as inefficient. This is not surprising, as though behinds contribute to team scoring, they also result in a loss of possession. The agreement levels outlined in both models indicates that alone the features used cannot fully explain the IFPR process. This may be a result of the features used not being able to fully capture aspects of technical performance, or potentially because the subjective assessors of performance consider more in depth performance actions, other contextual information (i.e., strength of opponent, expected match outcome) or are influenced by their own individual biases.

The recursive partitioning and regression tree model provides a visual representation of what performance indicators subjective raters tend to associate with better or worse performances. This is particularly visible by conceptualising the explanations of the highest and lowest IFPR values within each of the trees (i.e., the limbs stemming from the root node to the highest or lowest outcome variable of each recursive partitioning and regression tree). Whilst we observe that for the more frequently occurring IFPR outcome variables, performance rating can be explained in various ways, by various combinations of associated performance indicators. However, despite each recursive partitioning and regression tree (full model and player role specific models) incorporating six or more of these features, explanation of performances which are associated with highest or lowest IFPR values are explained by just the features

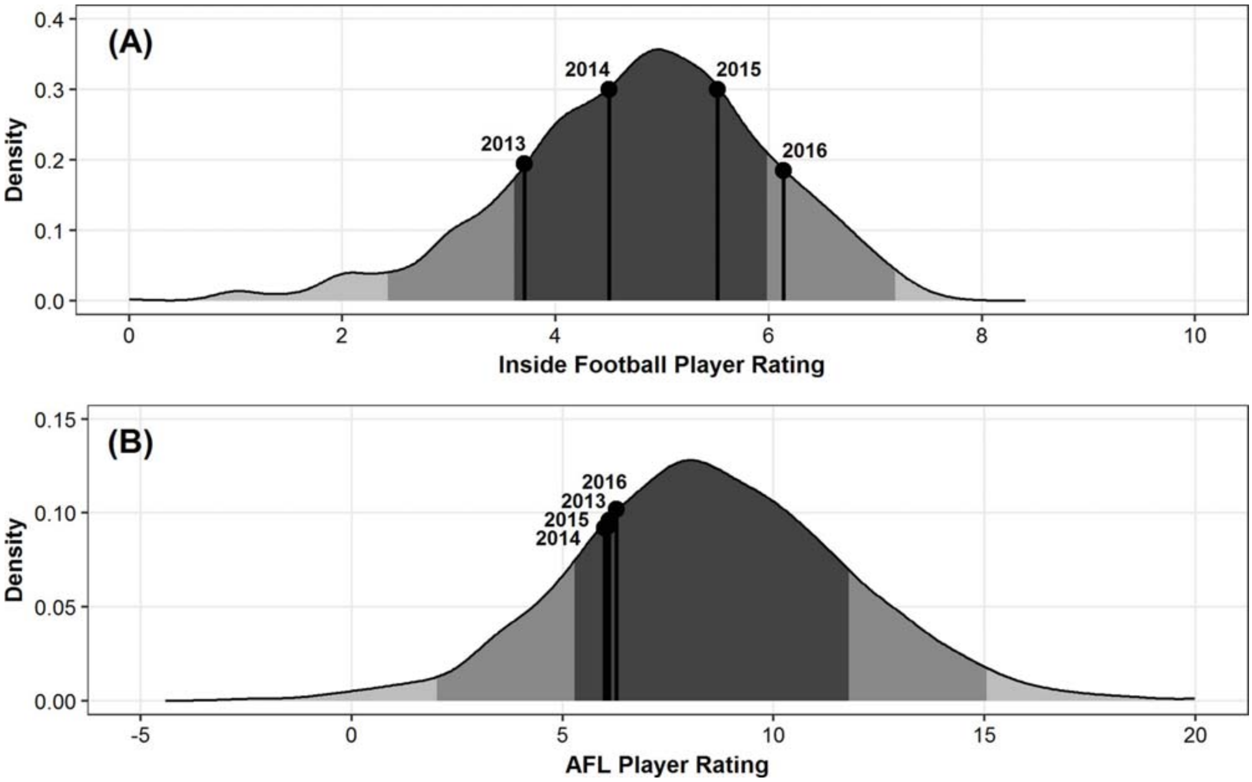

Fig 8. Ben Jacobs' average season ratings in comparison to the distribution of all player's average ratings. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013–2017 AFL seasons. Dark grey indicates mean ± SD, medium grey indicates one to two SD, and light grey indicates two plus SD.

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kicks, handballs and one or two other features for all player roles, except rucks which has three other features. This explanation of performance associated with the highest and lowest ratings aligns with previous research, whereby subjective evaluation of performance has been shown to rely on the presence of noticeable features that are specific to a player's role, and are easily brought to mind [8, 40]. For example, a specific instance of a positively associated noticeable feature in this study is goals for key forwards; whereby the model can explain the subjective rating of performance for players who kick four or more goals, irrespective of any other features.

Applications of these models have the potential to be beneficial in supporting the decision making processes in professional AF organisations. Figs 7 and 8 provide specific comparisons of how the subjective and objective evaluations of player performance outlined in Table 4 can be compared, and visualised. Specifically Fig 7 indicates that the player is objectively rated more highly across all four seasons in comparison to the subjective ratings system. Conversely, Fig 8 indicates that whilst the subjective rating system shows the individuals performance has progressed across his four seasons, the objective rating system indicates that performance has remained very similar. Without the ability to unequivocally identify the reasons for these inconsistencies, this highlights the importance of considering both subjective and objective measures when evaluating player performance.

In an applied setting, these findings advocate for performance evaluators and key decision makers (i.e., coaches, player scouts) to utilise both types of evaluations, and to be aware of their differences. Further, it also encourages the need for these key decision makers to be aware of the various reasons which could account for these differences, as well as the tendencies of the subjective performance assessors. As an example, the objective measure may not capture and fully account for certain aspects of the game, such as off-ball defensive acts, which would be important to know when evaluating individual players who have a specific role to negate an opposition player. Alternately, the subjective assessor may be prone to certain biases, such as a personal bias, and may consistently under- or over-rate certain players.

Some limitations of this study should also be noted. Though the mixed model approach in this study was able to account for repeated measures in the dataset, the recursive partitioning and regression tree model did not. Despite this limitation, as the results of the linear mixed model indicated minimal effects from the repeated measures variables, the recursive partitioning and regression tree model was subsequently used due to its interpretability as an applied application, and its ability identify non-linear trends. Another limitation is that not all available performance indicators were used to construct the models. Future research could look to include these, as well as other factors such as anthropometric features to further analyse subjective ratings of player performance in AF. Specifically, future research should target the subjective ratings of key decision makers within applied sporting organisations (i.e., coaches and scouts), to further understand the validity and reliability of their organisational decision making processes.

Conclusions

The models developed in this study provide an explanation of subjective analyses of performance in AF. Specifically, it demonstrates that subjective perceptions of performance can be somewhat accurately explained whilst considering a small number of performance indicators specific to a player's role. Further, though there is an ongoing development of objective data and player performance measures in both AF and wider team sport literature, the results of this study support the notion that overall player performance evaluations should consider both subjective and objective assessments in a complementary manner to accurately evaluate player performance.

Supporting information

S1 Dataset. De-identified dataset of all players.
(XLSX)

S1 Fig. Classification tree model explaining Inside Football Player Ratings for General Defenders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S2 Fig. Classification tree model explaining Inside Football Player Ratings for General Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S3 Fig. Classification tree model explaining Inside Football Player Ratings for Key Defenders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S4 Fig. Classification tree model explaining Inside Football Player Ratings for Key Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S5 Fig. Classification tree model explaining Inside Football Player Ratings for Midfielders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S6 Fig. Classification tree model explaining Inside Football Player Ratings for Midfield Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

S7 Fig. Classification tree model explaining Inside Football Player Ratings for Rucks from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.
(TIF)

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Supervision: Stephanie Kovalchik, Sam Robertson.

Visualization: Sam McIntosh.

Writing – original draft: Sam McIntosh.

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GRADUATE RESEARCH CENTRE

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I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

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Signature	**Date**

3. CO-AUTHOR(S) DECLARATION

In the case of the above publication, the following authors contributed to the work as follows:

The undersigned certify that:

1. They meet criteria for authorship in that they have participated in the conception, execution or interpretation of at least that part of the publication in their field of expertise;

2. They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;

3. There are no other authors of the publication according to these criteria;

4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and

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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Stephanie Kovalchik	5	Assisted with methodology design. Feedback and revisions for methodology.	Stephanie Kovalchik Digitally signed by Stephanie Kovalchik Date: 2019.09.05 12:13:20 +10'00'	5/9/19
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.	Sam Robertson Digitally signed by Sam Robertson Date: 2019.08.19 20:36:46 +10'00'	19/8/19

Comparing subjective and objective evaluations of player performance in Australian Rules football

6.1 Abstract

Player evaluation plays a fundamental role in the decision-making processes of professional sporting organisations. In the Australian Football League, both subjective and objective evaluations of player match performance are commonplace. This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance. A secondary aim was to compare subjective and objective ratings of player performance. Inside Football Player Ratings (IFPR) and AFL Player Ratings were collected as subjective and objective evaluations of player performance, respectively, for each player during all 1026 matches throughout the 2013-2017 AFL seasons. Nine common player performance indicators, player role classification, player age and match outcomes were also collected. Standardised linear mixed model and recursive partitioning and regression tree models were undertaken across the whole dataset, as well as separately for each of the seven player roles. The mixed model analysis produced a model associating the performance indicators with IFPR at a root mean square error of 0.98. Random effects accounting for differences between seasons and players ranged by 0.09 and 1.73 IFPR each across the five seasons and 1052 players, respectively. The recursive partitioning and regression tree model explained IFPR exactly in 35.8% of instances, and to within 1.0 IFPR point in 81.0% of instances. When analysed separately by player role, exact explanation varied from 25.2% to 41.7%, and within 1.0 IFPR point from 70.3% to 88.6%. Overall, kicks and handballs were most associated with the IFPR. This study highlights that a select few features account for a majority of the variance when explaining subjective ratings of player performance, and that these vary by player role.

Australian Football League organisations should utilise both subjective and objective assessments of performance to gain a better understanding of the differences associated with subjective performance assessment.

6.2 Introduction

Player evaluation plays a fundamental role in the decision-making processes of professional sporting organisations, including player monitoring, team selection, player contracting and scouting (Robertson et al., 2016; Ryoo, Kim & Park, 2018; Woods, Robertson, Collier, Swinbourne & Leicht, 2018). Despite widespread and available objective data within professional team sports, a reluctance of key decision makers to utilise these measures to develop and integrate decision support systems within their organisations remains (Alamar & Mehrotra, 2011; Hunt, Haynes, Hanna & Smith, 1998; Robertson et al., 2017). Despite this reluctance, there has been various literature outlining the benefits of considering objective evaluations of performance to support organisational decision-making processes (Carling et al., 2008; Pappalardo et al., 2017; Woods, Robertson, et al., 2018). Though these studies proclaim the benefits of objective evaluations (i.e., reliability and consistency), they each emphasise the importance of utilising both objective and subjective evaluations of performance in a complementary manner, to highlight whether inconsistencies exist between the evaluations and to ultimately improve player evaluation.

Australian Rules football (AF) is a dynamic invasion team sport played on a large oval field between two opposing teams consisting of 22 players each (18 on the field and four interchange). Due to the dynamic nature of the sport and the complex interactions which occur in AF, individual performance is difficult to analyse, both subjectively and objectively (Gerrard, 2007; McIntosh et al., 2018b). Despite this, various objective player performance measures have been created based on player performance in the elite competition of AF, the Australian Football League (AFL). Examples within the notational analysis literature include Stewart et al. (2007) who created a player ranking model by identifying the most important performance indicators, and including those with the strongest relationship to team winning margin. Heasman et al. (2008) created a player impact rating which assigned numerical values to each performance indicator relative to its perceived worth. These values were then weighted relative to environmental situations of the match, and adjusted relative to a player's time on ground.

Various objective player performance measures also exist for commercial purposes. Examples include the 'AFL Player Rankings' and the 'AFL Player Ratings', which are both produced by statistics provider Champion Data (Champion Data Pty Ltd., Melbourne, Australia). The former takes a similar approach to that of Stewart et al. (2007), however extends this model to include over 50 variables (Herald Sun, 2016), and is used for the fantasy competition 'SuperCoach' (www.supercoach.heraldsun.com.au). The latter takes an alternate approach to most player performance rating systems, and is based on the principle of field equity. In this system, each action is quantified relative to how much the action increases or decreases their team's expected value of scoring next (Jackson, 2009). A player's overall performance is then measured by the overall change in equity that is created by that player's actions during the game (Jackson, 2009).

Subjective analyses of performance are also commonplace within the AFL. Examples include the AFL Coaches Association award and the AFL's award for the fairest and best player

(Charles Brownlow Medal). Votes for each of these awards are cast at the conclusion of each match, based on the players deemed most influential during the match. Votes for the AFL Coaches Association award are cast by the senior coaches from both competing teams, and votes for the fairest and best player are cast by the field umpires. Further, various clubs use subjective coach ratings as a way of determining club based awards (Fox Sports, 2018), and various media sources publish subjective ratings for public interest.

A common criticism of player performance evaluation in AF, as well as other team sports (i.e., basketball), is their bias towards players whose specific role involves being more frequently involved in the play, enabling their actions to have a more tangible effect on performance evaluation (Martínez & Martínez, 2011; Niall, 2018). These biases have been noted within the notational team sport literature in relation to both subjective and objective player performance analyses (Heasman et al., 2008; McHale et al., 2012). For AF, this specifically relates to midfield players whose role is more centred on following the play to obtain/maintain possession of the ball and improving their team's field position. Previous objective player performance measures have combatted this by suggesting that player performance comparisons should be only made within players who play the same player roles (Heasman et al., 2008). Similar suggestions have been made in other team sports such as rugby union (James et al., 2005).

Despite frequent studies in the team sport notational analysis literature looking to encourage the use of objective performance rating systems (McHale et al., 2012; McIntosh et al., 2018b; Radovanović et al., 2013), very few studies have looked specifically at identifying the specific mechanisms behind subjective evaluation of individual performance in team sports. Pappalardo et al. (2017), analysed human evaluations of elite soccer performance using performance indicators and contextual information relating to each match performance. The authors illustrated that subjective ratings of performance were biased towards specific performance indicators, as well as contextual factors such as the outcome of a game, and the expected outcome of a game as estimated by bookmakers. Their findings indicated that in order to improve overall performance evaluations, player analysis should be a balance between objective performance measures and subjective values such as insights from qualitative skill qualities. These findings are indicative of those in other fields, which have shown that humans are susceptible to many errors and biases in decision-making, and have limits to the amount of information they can comprehend (Grove et al., 2000; Miller, 1956).

In AF, the majority of research on evaluating player performance has had a specific focus on assessing performance indicators in order to explain or predict playing performance (Heasman et al., 2008; McIntosh et al., 2019b; Stewart et al., 2007; Tangalos et al., 2015; Woods et al., 2016; Woods, Veale, Collier & Robertson, 2017). Further to this, various other research in AF has been undertaken in other areas, such as assessing the relationship between performance indicators and match outcome (Robertson, Back, et al., 2015; Robertson et al., 2016; Young, Luo, Gastin, Tran, et al., 2019), playing position (McIntosh et al., 2018a; Woods, Veale, et al., 2018), and trends in game-play (Woods, Robertson, et al., 2017).

This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance in the AFL. A secondary aim was to compare subjective and objective ratings of player performance. The rationale for this study was to identify the relationship between subjective ratings of performance and the most basic comprehendible performance indicators, in order to add to the existing understanding of the extent to which human decisions are related to measurable aspects of a player's performance. The methodologies are expressed as an exemplar of what could be implemented within professional AF organisations using their own specific subjective rating processes. An understanding of these insights could be beneficial in supporting organisational decisions relating to weekly team selection, player recruitment, as well as player contracting and financial remuneration; each which have ramifications on team outcomes.

6.3 Methods

6.3.1 Data

Two separate measures of player performance were collected for each player during 1026 matches played throughout the 2013-2017 AFL seasons. This included 22 matches played by each team during the regular season, as well as a total of nine matches played throughout the finals series each season. One match was abandoned prior to play during the 2015 season. Further, the eight drawn matches that occurred throughout the 2013–2017 seasons were removed from the analyses.

The IFPR were obtained from http://www.aflplayerratings.com.au, which is a subjective measure of player performance, rated continuously from zero to ten, based on human interpretation of a player's performance ('Inside Football' is the commercial publication for these publically available player ratings). The ratings for each match were completed by a single AFL accredited journalist who was covering the game for Inside Football (most of whom had 10+ years in the industry). The journalist covering the game was at the ground in the majority of instances, and ratings were provided immediately post-match. The AFL Player Ratings were acquired from Champion Data (also available from http://www.afl.com.au/stats), which is an objective measure of player performance, rated on an open-ended continuous scale, and based on the principle of field equity (Jackson, 2009). The rating process is derived from contextual information collected in real time by trained Champion Data staff (corrected post-game), and is determined by how much each player's actions increase or decrease their team's expected value of scoring (Jackson, 2009). The validity and reliability of the data provided by Champion Data is not publicly available. However, previous research conducted in AF has reported the validity of the performance indicators collected by Champion Data as high (O'Shaughnessy, 2006), and the reliability (as determined by an external assessment) as very high (ICC ranged from 0.947–1.000 for the included performance indicators) (Robertson et al., 2016). Nine player performance indicators were collected from http://www.afl.com.au/stats, for each player and match included in the dataset. These indicators were selected due to being widely reported and available, as well as being previously reported in the literature (Robertson, Back, et al., 2015; Robertson et al., 2016; Stewart et al., 2007). These performance indicators and their definitions are outlined in Table 6.1. Player role classifications were collected for each player, based on Champions Data's classification for each player at the end of each respective AFL season. These classifications are defined in Table 6.2. Additionally, a player's age for each corresponding season (range: 18 to 40), and the match outcome for each match (Win and Losses; dummy coded as 1 and 0, respectively) were also collected.

Table 6.1 Definitions of the Australian Rules football performance indicators used in this study.

Performance Indicator	**Definition**
Kick	Disposing of the football with any part of the leg below the knee.
Handball	Disposing of the football by hitting it with the clenched fist of one hand, while holding it with the other.
Mark	Catching or taking control of the football after it has been kicked by another player a distance of at least 15 metres without touching the ground or being touched by another player.
Tackle	Taking hold of an opposition player in possession of the ball, in order to impede his progress or to force him to dispose of the ball quickly.
Free For	An infringement in favour of the player as called by the umpire.
Free Against	An infringement against the player as called by the umpire.
Hitout	A tap by a ruckman after a ball up or bounce by the umpire.
Goals	The maximum possible score (6 points) achieved by kicking the ball between the two goalposts without touching a post or any player.
Behinds	A score worth one point, achieved by the ball crossing between a goalpost and a behind post, or by the ball hitting a goalpost, or by the ball being touched prior to passing between the goalposts.

Table 6.2 Champions Data's descriptions of the seven player roles used in this study.

Player Roles	Description
General Defender	Plays a role on opposition small-medium forwards and usually helps create play from the backline
Key Defender	Plays on opposition key forwards with the primary role of nullifying his opponent
General Forward	Plays predominantly in the forward half of the ground but with more freedom than a key forward
Key Forward	Plays predominantly as a tall marking target in the forward line
Midfielder	Spends the majority of time playing on the ball or on the wing
Midfield Forward	Splits time equally between the forward line and the midfield. Often lines up on the half-forward flank but plays a significant amount of time in the midfield
Ruck	Has the primary role of competing for hit-outs at a stoppage

6.3.2 Statistical analysis

Descriptive statistics (mean and standard deviation) were calculated for each of the two player rating measures, as well as for each respective player role. To determine the variation between the two rating systems, as well as each of the playing roles, the coefficient of variation was calculated for each. To determine the level of association between the two player rating systems and each of the features univariately (all performance indicators, as well as age and match outcome), correlational analyses were undertaken. This analysis was undertaken using the *Hmisc* package (Harrell Jr, 2017) in the R statistical computing software version 3.3.2 (R Core Team, 2016), and visualised using a correlogram.

A linear mixed model analysis was undertaken to determine the extent to which each of the features explained IFPR. This particular approach was used to control the variability created by the repeated measures on each player. This analysis was undertaken using the *lme4* package

(Bates et al., 2015). All factors (besides position) were standardised and centred with a mean = 0 prior to the analysis to allow for Beta coefficient comparisons. In the model, player and season were treated as separate random effects, whilst all other factors were considered as fixed effects.

A recursive partitioning and regression tree model (Breiman et al., 1984; Gupta et al., 2017) was undertaken as a secondary method to determine the extent to which each of the features explained IFPR. This analysis was undertaken using the *rpart* package, which uses the CART algorithm (classification and regression trees) (Therneau et al., 2015). A minimum of 100 cases were needed for each node to split, and the complexity parameter was set at 0.001 in order to maximise the number of outcome variables in the model. These measures were employed in order to avoid overfitting and to produce a more parsimonious model. Data were split whereby the 2013-2016 seasons were used to train the model, which was then subsequently tested on the 2017 season. Results of the model were displayed using a tree visualisation and a histogram outlining the model accuracy. Additionally, the recursive partitioning and regression tree analysis was conducted firstly on the whole dataset and then separately for each of the seven respective player roles.

A comparison of the IFPR and AFL Player Ratings was created for two specific players as a practical decision support application. Specifically, the deviation of each player's season mean ratings was compared to the overall sample mean for each rating system. This application allowed for a descriptive analysis and visualisation of the difference in evaluation between the subjective and objective systems.

6.4 Results

Descriptive statistics of each player role for both the IFPR and the AFL Player Ratings measures are presented in Figure 6.1. The overall mean and standard deviation of each rating system was 5.25 ± 1.73 for the IFPR, and 9.65 ± 5.58 for the AFL Player Ratings. The coefficient of variation for each system was 32.9% and 57.8%, respectively. The results of the Pearson's correlation analysis indicated a moderate association (r = 0.60) between the AFL Player Ratings and the IFPR. Further, the IFPR and marks both showed moderate associations (r = 0.64 and r = 0.53) with kicks. All of the remaining associations were r < 0.50 and are outlined in Figure 6.2. Figure 6.3 outlines the distribution on AFL Player Ratings along the various levels of IFPR, indicating that as the IFPR increases, the mean AFL Player Ratings increases and the distribution becomes more spread.

The results of the linear mixed model are outlined in Table 6.3. All features except for frees against, behinds and age contribute significantly to the model (p < 0.001), with kicks and handballs having the highest Beta coefficients of 0.844 and 0.646, respectively. The model produced a root mean square error of 0.98 in association with the IFPR. The random effect accounting for the difference between seasons ranged by 0.09 IFPR across the five seasons, indicating minimal variation. The random effect accounting for differences between players ranged by 1.73 IFPR across the 1052 players, indicating that the mixed model varied substantially in its ability to explain player performance for all players.

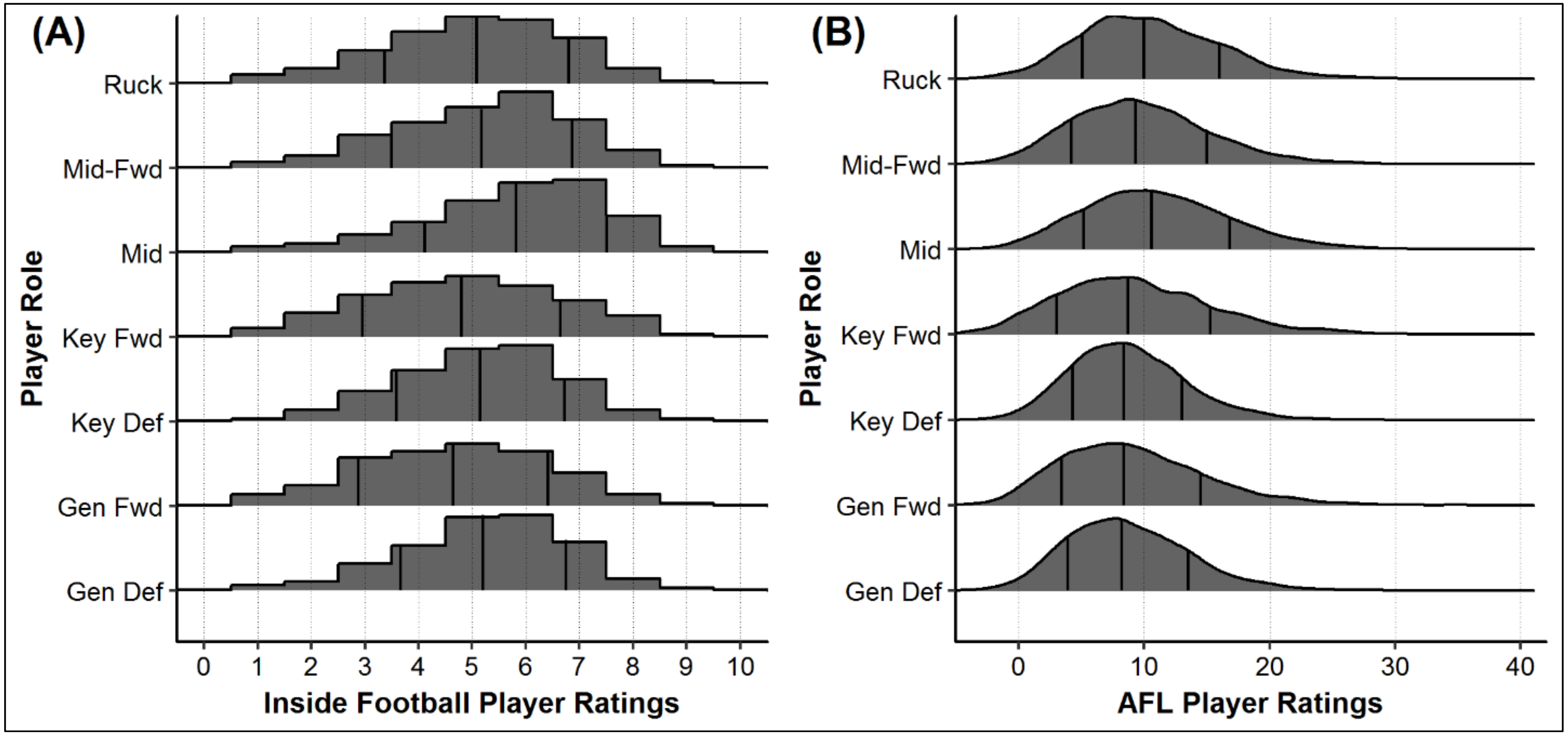

Figure 6.1 **Standardised density distribution (%) of each player role. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013-2017 AFL seasons. Vertical lines indicate mean and ± one standard deviation.**

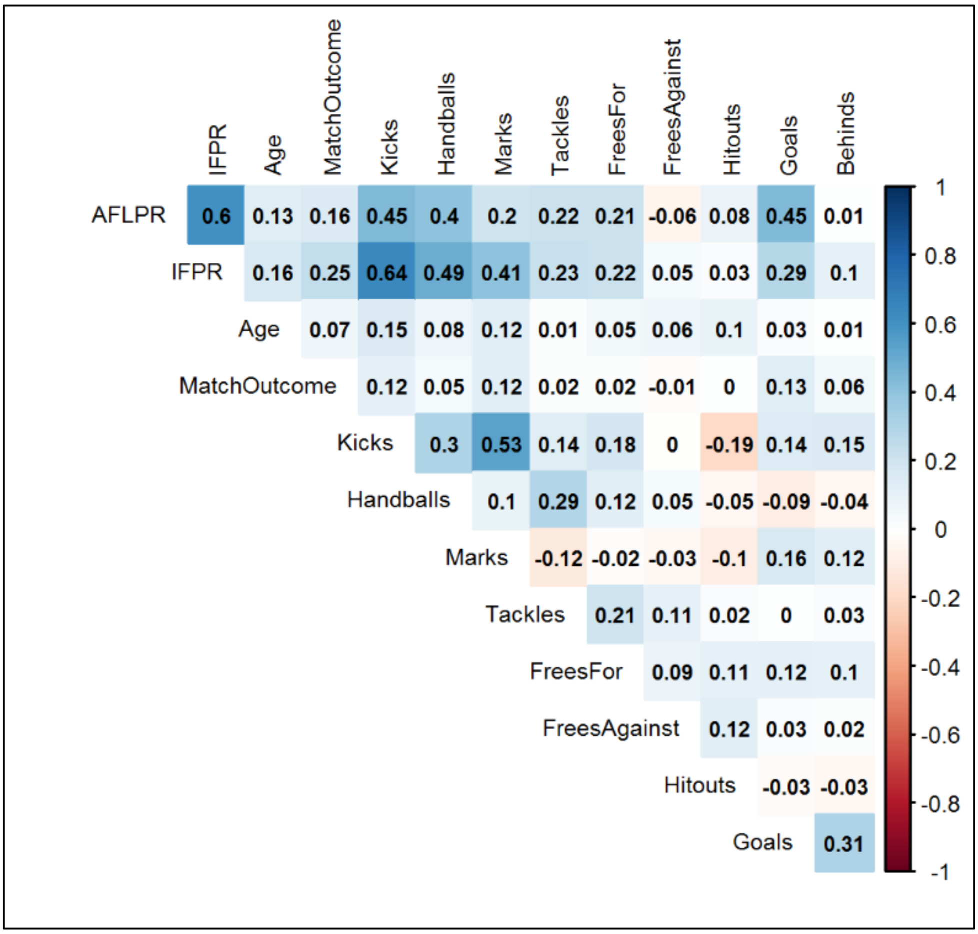

Figure 6.2 **Correlogram outlining the Pearson correlation coefficients (*r*) between all features used within the study.**

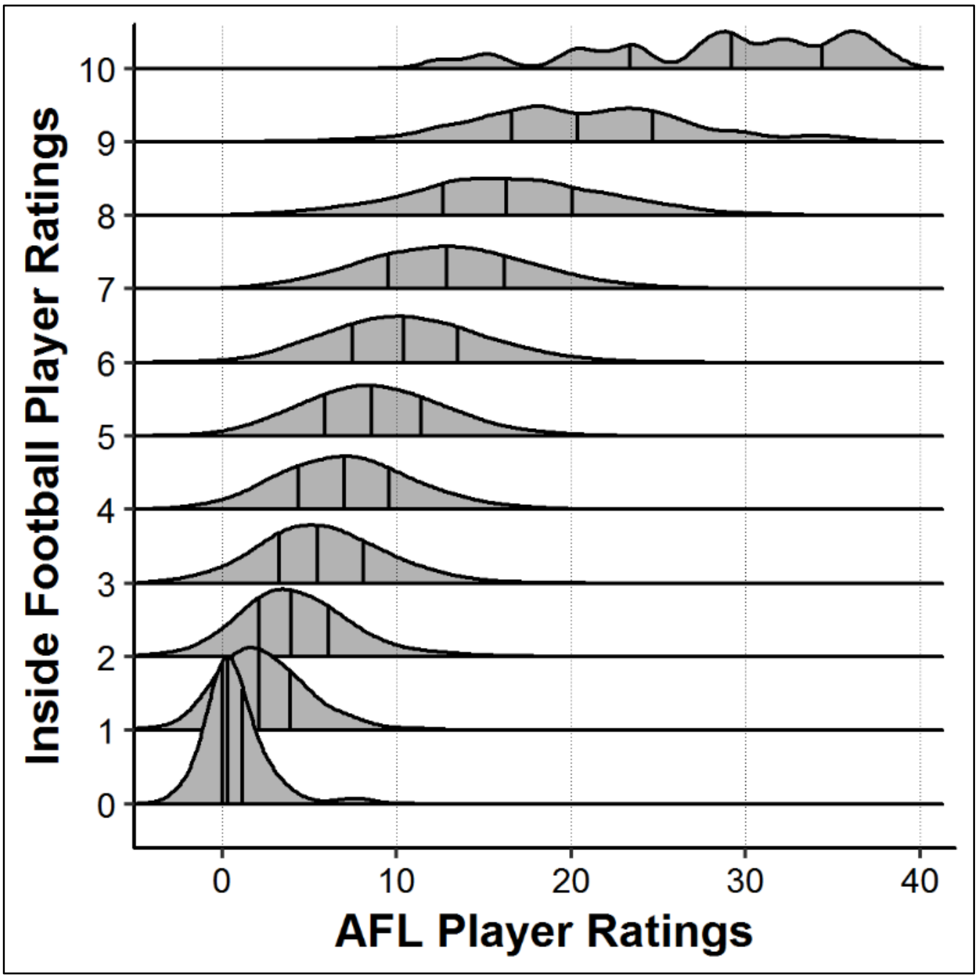

Figure 6.3 Standardised density distribution (%) of AFL Player Ratings across levels of Inside Football Player Ratings. Vertical lines indicate mean and ± one standard deviation.

Table 6.3 Results of the linear mixed model (dependent variable is "Inside Football Player Ratings").

Performance Indicator	*β*	Std. Error	*P*
Kicks	0.844	0.007	< 0.001
Handballs	0.646	0.006	< 0.001
Marks	0.091	0.006	< 0.001
Tackles	0.150	0.006	< 0.001
Frees For	0.047	0.005	< 0.001
Frees Against	-0.004	0.005	0.467
Hitouts	0.290	0.011	< 0.001
Goals	0.510	0.006	< 0.001
Behinds	0.004	0.005	0.473
Match Outcome	0.217	0.005	< 0.001
Age	0.011	0.010	0.261
Positional role (General Forward)	-0.406	0.026	< 0.001
Positional role (Key Defender)	0.486	0.030	< 0.001
Positional role (Key Forward)	-0.330	0.035	< 0.001
Positional role (Midfield)	-0.310	0.023	< 0.001
Positional role (Midfield Forward)	-0.310	0.028	< 0.001
Positional role (Ruck)	-0.321	0.054	< 0.001

Reference level for positional role: General Defender.

The full recursive partitioning and regression tree model is presented in Figure 6.4. Despite having 38 terminal nodes, only the features relating to ball disposal (kicks and handballs), scoring (goals and behinds), match outcome and hitouts contribute to the model. The splitting of the nodes within each branch indicates that having a greater total count of each performance indicator results in a higher rating of performance, except for behinds. None of the terminal nodes explain the outcome variables zero, nine or ten. The results of this model are outlined in Figure 6.5 and display that the IFPR could be explained exactly in 35.8% of instances, and within 1.0 IFPR point 81.0% of the time. The positive x-axis variables indicate that the model-expected IFPR was higher than the actual IFPR. Conversely, the negative x-axis variables indicate that the model-expected IFPR was lower than the actual IFPR.

Appendices C.1-C.7 outline the separate recursive partitioning and regression tree models based on each player role. As with the full model, none of the terminal nodes explain the outcome variables zero or ten; however the models based on Key Forwards and Midfielders do explain the outcome variable nine. Further, the model based on Key Defenders also excludes the outcome variables one and eight. Each of the separate models included six or more features, with kicks and handballs featuring heavily in all. Kicks was the root node in all models except for Rucks and Key Forwards, where hitouts and goals where the root node in each, respectively. The most notable additional changes from the full model were that goals featured frequently in the models for Key and General Forwards, marks featured frequently in Key and General Defenders, as well as Key Forwards, tackles for General Defenders, Key Forwards and Midfielders, and hitouts for Ruckmen. The range of accuracy for explaining IFPR exactly in these separate models varied from 25.2% for Key Defenders to 41.7% for Midfielders. The accuracy within 1.0 IFPR point either side varied from 70.3% for Key Defenders to 88.6% for Midfielders.

Figure 6.6 outlines the distribution of IFPR and AFL Player Ratings for winning and losing teams across the five seasons. The abovementioned random effects accounting for player differences provide an indication of the individual players who were most consistently under- and over-rated as estimated by the linear mixed model, after adjusting for the fixed effect factors. Two individuals were selected, with a comparison of subjective and objective evaluations of their performance undertaken as an exemplar of the application. Specifically, in order to compare their evaluations between the two rating systems on different scales, the deviation of their seasonal mean rating from the overall sample mean were calculated for each system. Table 6.4 outlines the deviation of their seasonal mean ratings from the overall sample mean of rating values for the two respective players. Additionally, Figure 6.7 and Figure 6.8 outline how this could be visualised for ease of interpretability in an applied setting.

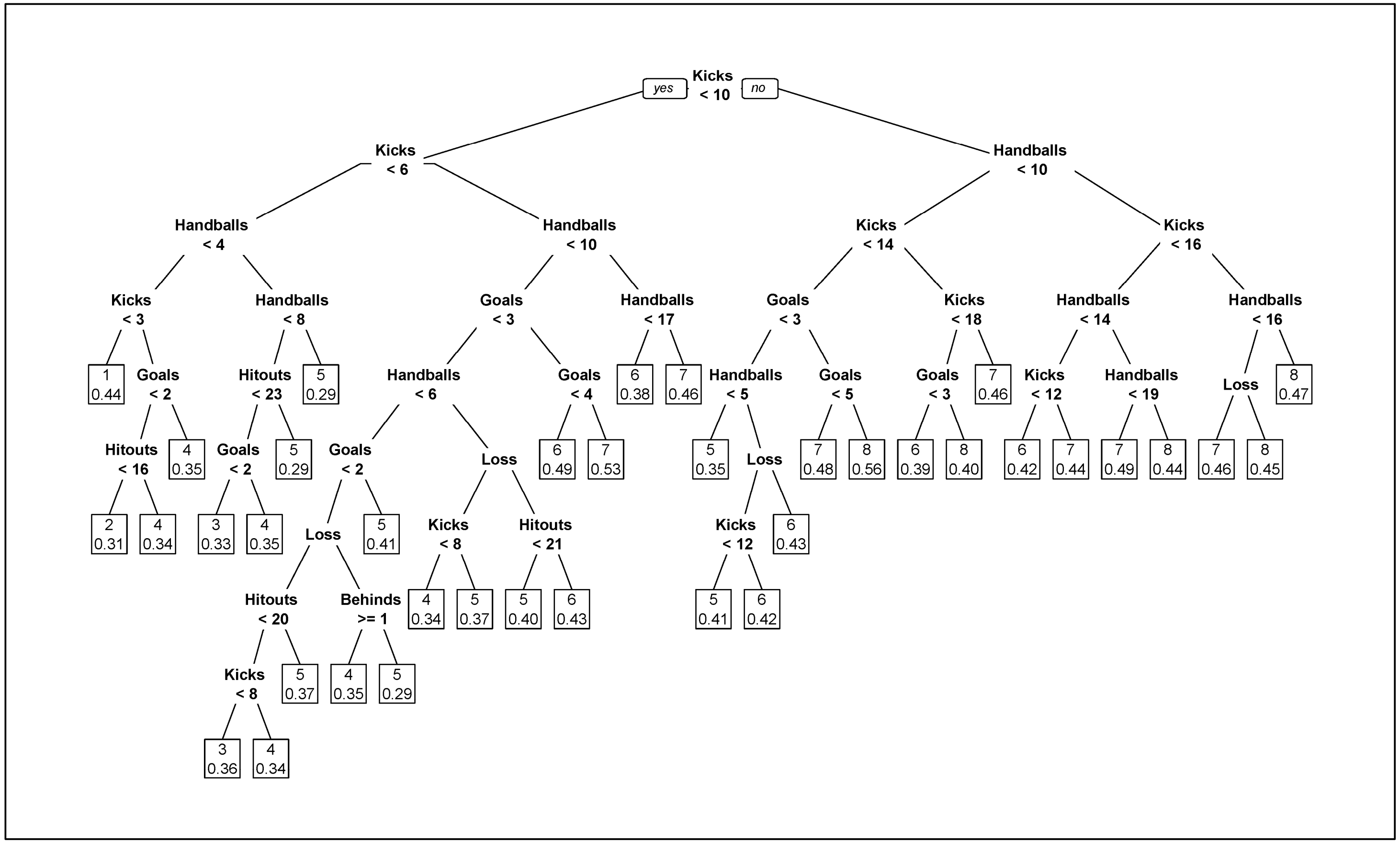

Figure 6.4 **Recursive partitioning and regression tree model explaining Inside Football Player Ratings from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**

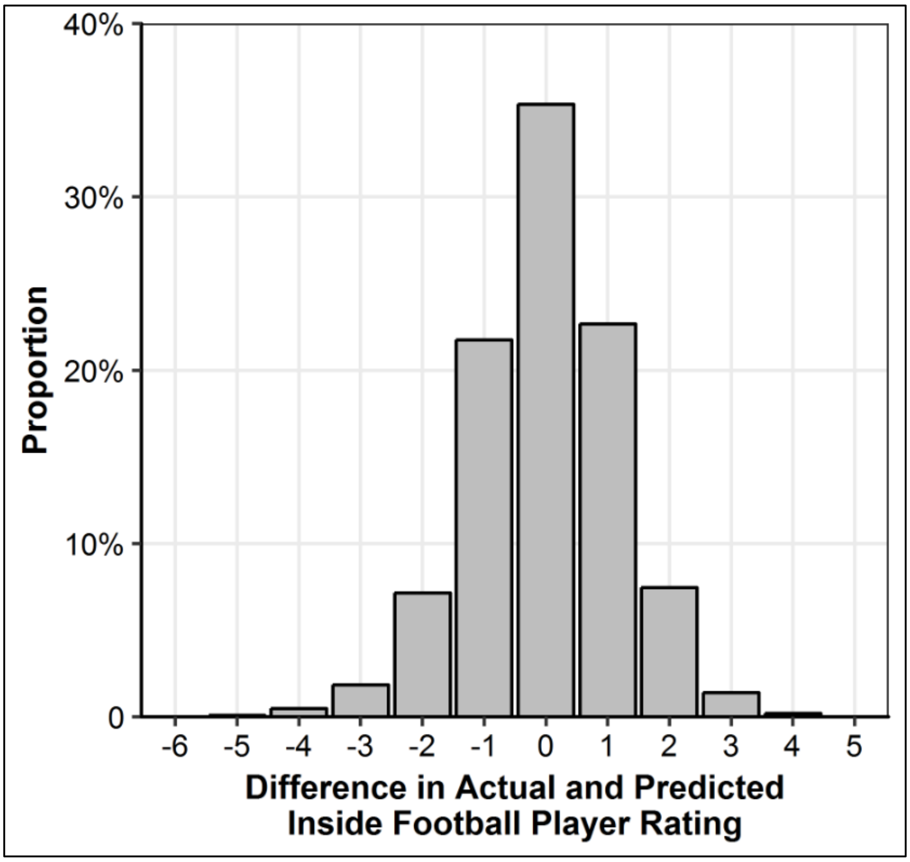

Figure 6.5 Difference in actual and model-expected Inside Football Player Ratings.

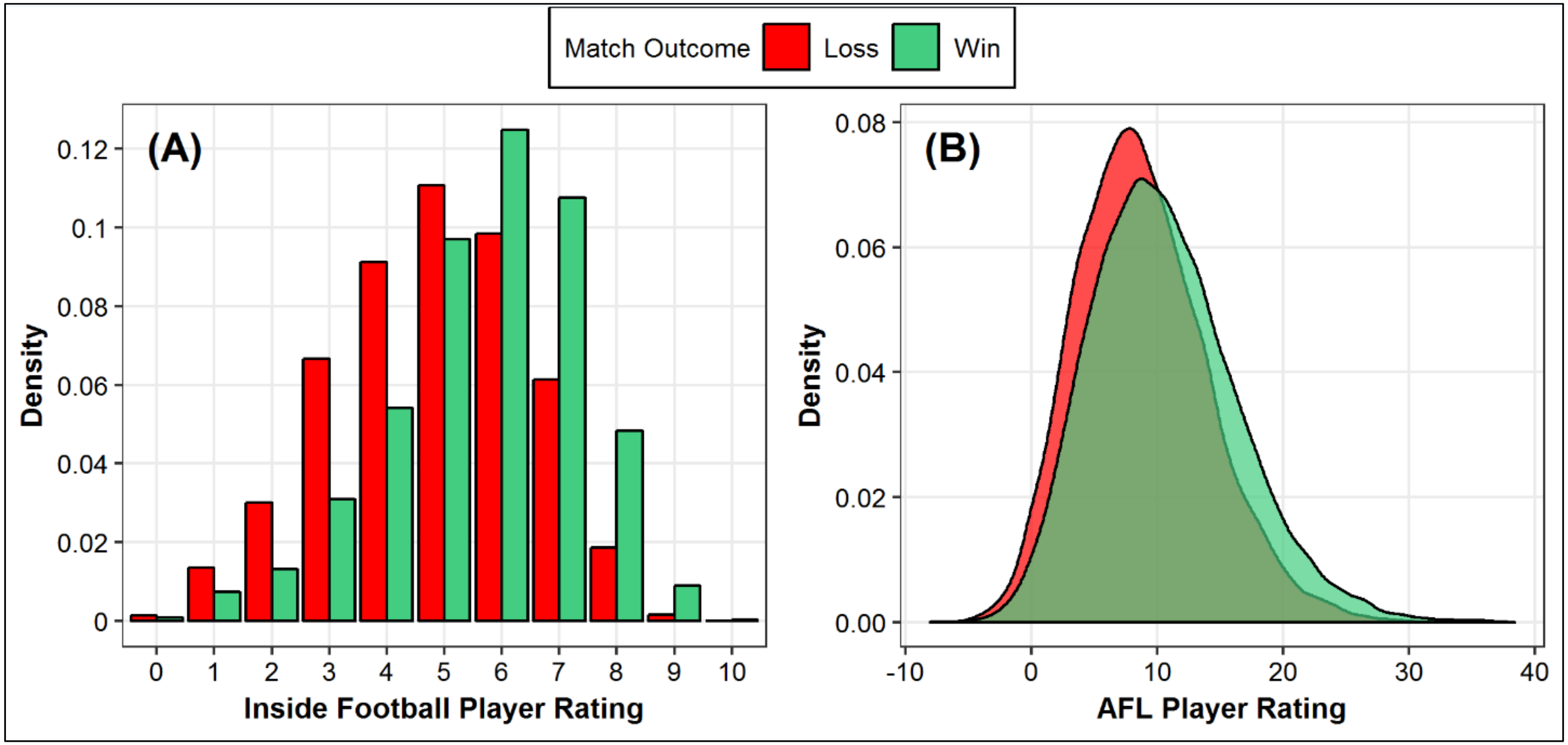

Figure 6.6 **Density of ratings given for all players based on match outcome (Wins and Losses). (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013-2017 AFL seasons.**

Table 6.4 Variation of seasonal mean ratings from the overall sample mean ratings for Paul Puopolo and Ben Jacobs.

	Paul Puopolo			Ben Jacobs		
Season	**IFPR SD from Sample Mean**	**AFL Player Rating SD from Sample Mean**	**Difference in Deviation**	**IFPR SD from Sample Mean**	**AFL Player Rating SD from Sample Mean**	**Difference in Deviation**
2013	0.93	0.94	-0.01			
2014	0.37	0.60	-0.23	-0.91	-0.74	-0.17
2015	0.39	0.92	-0.53	-0.15	-0.78	0.63
2016	0.17	0.98	-0.81	0.60	-0.76	1.36
2017	-0.56	0.83	-1.39	1.07	-0.70	1.77

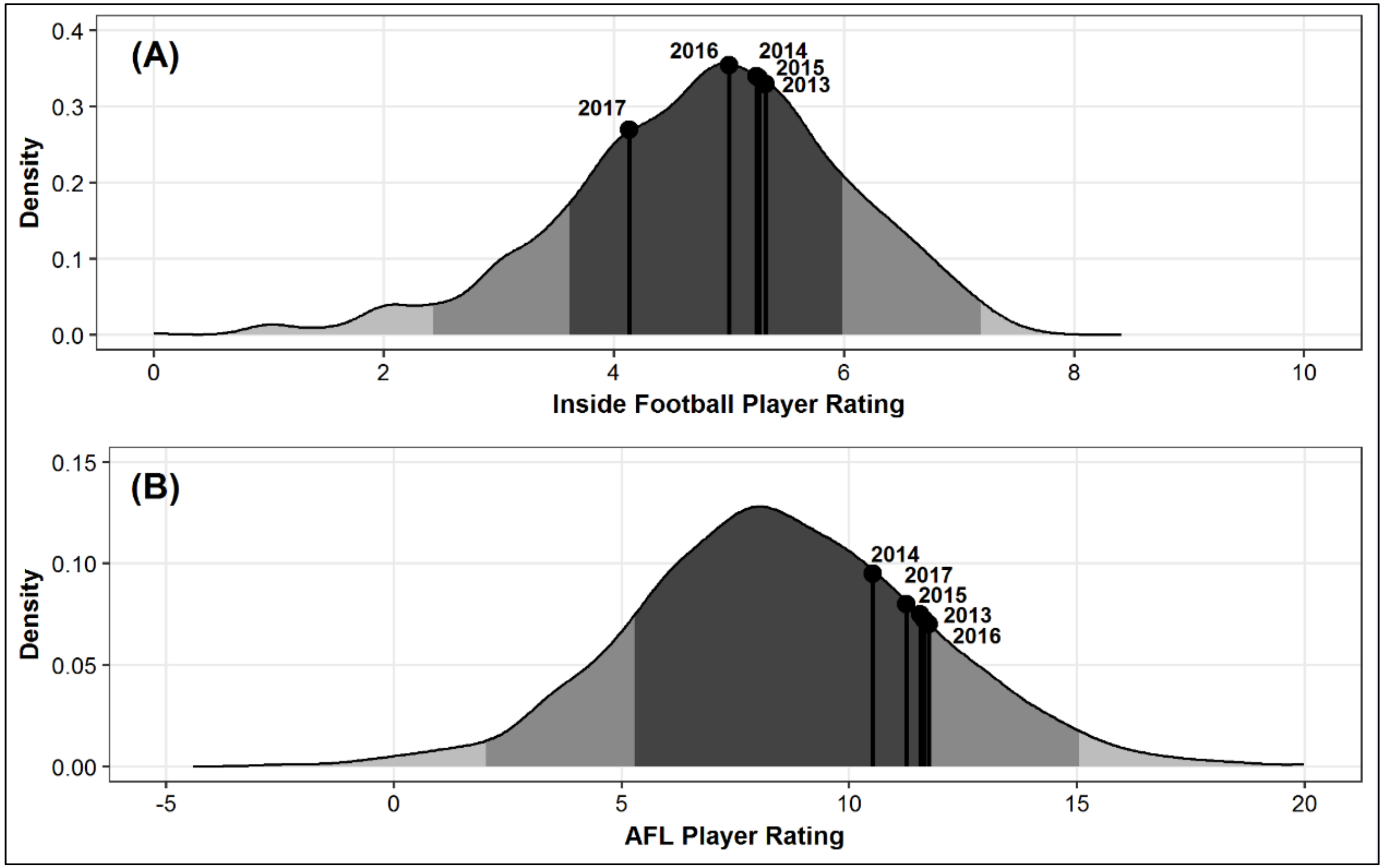

Figure 6.7 **Paul Puopolo's average season ratings in comparison to the distribution of all player's average ratings. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013-2017 AFL seasons. Dark grey indicates mean ± SD, medium grey indicates one to two SD, and light grey indicates two plus SD.**

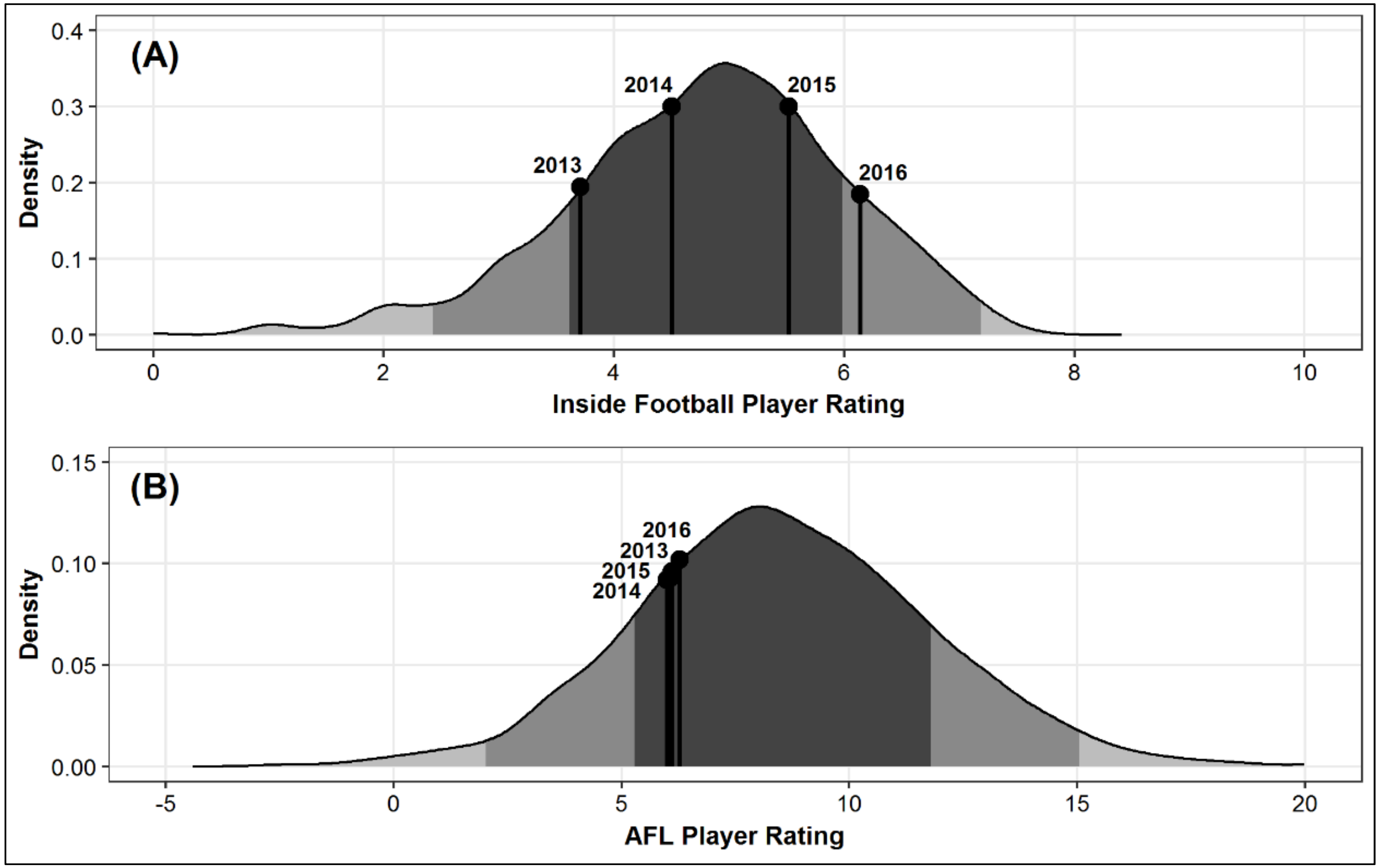

Figure 6.8 **Ben Jacobs' average season ratings in comparison to the distribution of all player's average ratings. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013-2017 AFL seasons. Dark grey indicates mean ± SD, medium grey indicates one to two SD, and light grey indicates two plus SD.**

6.5 Discussion

This study aimed to identify the extent to which performance indicators can explain subjective ratings of player performance. A secondary aim was to compare subjective and objective evaluations of player performance. To achieve the primary aim, two separate models were fit identifying the relationship between our exemplar subjective rating system, the IFPR, and the selected performance indicators. To achieve the secondary aim, a descriptive analysis and visualisation was conducted to outline the potential discrepancies noted between subjective and objective evaluations of player performance. Together, these methodologies are expressed as an exemplar of what could be implemented within professional AF organisation using their own specific subjective rating processes.

Inspection of the coefficient of variation for each playing role, and the descriptive statistics outlined in Figure 6.1 indicates that the distribution of ratings in the subjective IFPR system is more variable between each of the player role classifications, in comparison to the objective AFL Player Ratings system. In addition to this, in both ratings systems the mean values for midfielders are higher than that for all other player roles. This aligns with the aforementioned biases noted within both AF and the wider team sport literature (Heasman et al., 2008; Martínez & Martínez, 2011; Niall, 2018).

Both the linear mixed model and recursive partitioning and regression tree models provide an objective view of how subjective analyses of performance are explained. Each of the models reflect the results of the other, and outline that when explaining subjective assessment of performance, a small number of features account for a large majority of the variance. The changes seen in the recursive partitioning and regression tree model once analysed separately by position supports the notion that specific indicators differ between playing roles, indicating that controlling for player role when explaining player performance subjectively is important, to account for the roles specific to each positional group (Torgler & Schmidt, 2007). Further, both models display a negative association between behinds and expected IFPR, thus indicating that behinds might be viewed as inefficient. This is not surprising, as though behinds contribute to team scoring, they also result in a loss of possession. The agreement levels outlined in both models indicates that alone the features used cannot fully explain the IFPR process. This may be a result of the features used not being able to fully capture aspects of technical performance, or potentially because the subjective assessors of performance consider more in depth performance actions, other contextual information (i.e., strength of opponent, expected match outcome) or are influenced by their own individual biases.

The recursive partitioning and regression tree model provides a visual representation of what performance indicators subjective raters tend to associate with better or worse performances. This is particularly visible by conceptualising the explanations of the highest and lowest IFPR values within each of the trees (i.e., the limbs stemming from the root node to the highest or lowest outcome variable of each recursive partitioning and regression tree). Whilst we observe that for the more frequently occurring IFPR outcome variables, performance rating can be explained in various ways, by various combinations of associated performance indicators. However, despite each recursive partitioning and regression tree (full model and player role specific models) incorporating six or more of these features, explanation of performances which are associated with highest or lowest IFPR values are explained by just the features kicks, handballs and one or two other features for all player roles, except rucks which has three other features. This explanation of performance associated with the highest and lowest ratings aligns with previous research, whereby subjective evaluation of performance has been shown to rely on the presence of noticeable features that are specific to a player’s role, and are easily brought to mind (Pappalardo et al., 2017; Parrington, Ball & Macmahon, 2013). For example, a specific instance of a positively associated noticeable feature in this study is goals for key forwards; whereby the model can explain the subjective rating of performance for players who kick four or more goals, irrespective of any other features.

Applications of these models have the potential to be beneficial in supporting the decision-making processes in professional AF organisations. Figures 6.7 and 6.8 provide specific comparisons of how the subjective and objective evaluations of player performance outlined in Table 6.4 can be compared, and visualised. Specifically Figure 6.7 indicates that the player is objectively rated more highly across all four seasons in comparison to the subjective ratings system. Conversely, Figure 6.8 indicates that whilst the subjective rating system shows the individuals performance has progressed across his four seasons, the objective rating system indicates that performance has remained very similar. Without the ability to unequivocally identify the reasons for these inconsistencies, this highlights the importance of considering both subjective and objective measures when evaluating player performance.

In an applied setting, these findings advocate for performance evaluators and key decision makers (i.e., coaches, player scouts) to utilise both types of evaluations, and to be aware of their differences. Further, it also encourages the need for these key decision makers to be aware of the various reasons which could account for these differences, as well as the tendencies of the subjective performance assessors. As an example, the objective measure may not capture and fully account for certain aspects of the game, such as off-ball defensive acts, which would be important to know when evaluating individual players who have a specific role to negate an opposition player. Alternately, the subjective assessor may be prone to certain biases, such as a personal bias, and may consistently under- or over-rate certain players.

Some limitations of this study should also be noted. Though the mixed model approach in this study was able to account for repeated measures in the dataset, the recursive partitioning and regression tree model did not. Despite this limitation, as the results of the linear mixed model indicated minimal effects from the repeated measures variables, the recursive partitioning and regression tree model was subsequently used due to its interpretability as an applied application, and its ability identify non-linear trends. Another limitation is that not all available performance indicators were used to construct the models. Future research could look to include these, as well as other factors such as anthropometric features to further analyse subjective ratings of player performance in AF. Specifically, future research should target the subjective ratings of key decision makers within applied sporting organisations (i.e., coaches and scouts), to further understand the validity and reliability of their organisational decision-making processes.

6.6 Conclusion

The models developed in this study provide an explanation of subjective analyses of performance in AF. Specifically, it demonstrates that subjective perceptions of performance can be somewhat accurately explained whilst considering a small number of performance indicators specific to a player's role. Further, though there is an ongoing development of objective data and player performance measures in both AF and wider team sport literature, the results of this study support the notion that overall player performance evaluations should consider both subjective and objective assessments in a complementary manner to accurately evaluate player performance.

CHAPTER SEVEN – GENERAL DISCUSSION, CONCLUSIONS AND FUTURE DIRECTIONS FOR RESEARCH

Chapter Overview

In this chapter, the methodologies and results produced as part of this thesis are discussed, as well as the implementation of decision support systems within professional organisations. This chapter contains a general discussion (section 7.1), industry implementation (section 7.2), future directions (section 7.3) and conclusion (section 7.4) sections.

7.1 General Discussion

The overarching aim of this thesis was to model player performance data for organisational decision support in professional AF. Specifically, this thesis targets a niche area of the literature which exists surrounding modelling player performance data to explain individual player performance in AF. This thesis achieves that by creating new applications, as well as extending existing methodologies from other team sports to AF, utilising the elite competition the AFL. A primary motivation of this thesis was to create actionable intelligence (Morgan, 2016), through visualising the models in each study to provide meaningful information which could be used directly by those individuals in the organisational positions to best make effective use of it (i.e., coaches, contract managers, scouts). The thesis begins by investigating the validity of the official AFL Player Ratings system. This initial investigation (Chapter Three) was conducted to outline the viability of this system for use in further analyses. The following studies of this thesis (Chapters Four and Five) then focus on the use of this objective metric to create applications for supporting both short- and long-term organisational decisions. The final study of this thesis (Chapter Six) then focuses on comparing objective and subjective evaluations of player performance, in order to gain a better understanding of the differences associated between each form of performance assessment.

One of the primary contributions of this thesis are the insights derived from the model applications. Specifically, the different modelling approaches were conducted with practical application in mind to allow for applied use within the AFL. Prior to the research presented in this thesis, minimal work had been undertaken targeting the application of player performance data to support recruitment and list management decisions in AF. While player performance data has been previously used to summarise and quantify individual player match performance (Heasman et al., 2008; Stewart et al., 2007; Tangalos et al., 2015), no studies had used the player performance data to examine longitudinal player performance, or to compare subjective and objective assessments of player performance in professional AF.

The AFL is a multi-billion dollar sports industry, with substantial regulations around maintaining competitive balance across the competition (Gray & Jenkins, 2010). As such, there is a large emphasis by professional AF clubs and their key decision makers on improving the accuracy and efficiency in which organisational decisions are made, in order to gain and maintain a competitive advantage (Hickey, Shield, Williams & Opar, 2014; Robertson, Back, et al., 2015). This emphasis partially stems from improvements seen in other professional team sports, which have demonstrated that organisations can benefit substantially by employing methodical and disciplined approaches to change the way in which they approach decision-making tasks (Maymin, 2017; Ofoghi, Zeleznikow, MacMahon & Dwyer, 2013). Other factors driving this improvement include the increase in likeness drawn between sporting organisation processes, to that of established processes within other industry organisations, and the associated learning transfers which can be generated (Massey & Thaler, 2013; Woods, Robertson, et al., 2018). Specifically, Massey and Thaler (2013) outline that team sport is arguably a simpler domain for improving processes such as recruitment, due to the ability track the performance of selected and non-selected prospects both before and after recruitment (assuming non-selected prospects are selected by other teams). The benefits of improving the accuracy and efficiency of decision-making in other team sports and other industries has led to both improved team/organisation performance outcomes, as well as the financial gains associated with improved performance (Brynjolfsson & McElheran, 2016; Maymin, 2017; Ofoghi, Zeleznikow, MacMahon & Dwyer, 2013). As a result, this has created a greater demand for research into performance analysis processes to provide objective approaches to support decision-making tasks in AF (Robertson, Woods, et al., 2015).

Presently, there is a large amount of player performance data available at the elite level of AF, including match and training technical performance indicators and spatiotemporal parameters, as well as non-performance specific data such as physical testing and wellness data. However, the volume of applications created and published within the notational team sport literature is behind that of other invasion team sports. This reduced attention likely exists due to both the level of complexity determining objectively quantifiable outcomes in AF (Duch et al., 2010), as well as other professional sporting leagues having access to increased resources (Sarmento et al., 2014).

In section 2.3 it was outlined that the outcomes of this thesis did not intend to develop automated decision support systems; but rather to emphasise the importance of utilising relevant data and appropriate methodologies to create objective systems which could be used to support organisational decisions. Whilst the open-ended applications created as part of this thesis have their place within applied settings to provide descriptive exploration and quantitative recommendations in a visual format, there is also a place for more directed or closed decision support systems. These systems can be designed to provide support by specifically outlining the 'best' decisions for key decision makers (i.e., traffic-lighting type systems), allowing for certain organisational decision-making tasks to become a formalised process. A specific example of a closed decision support system in an applied team sport setting is that by Robertson et al. (2016), whereby a traffic-light system is used to indicate a direct recommendation as to the status of each athlete with respect to performance or training availability.

Despite outlining the applicability of objective models for the support of decisions relating to player selection, recruiting and contracting in this thesis, very little has addressed how these decisions can be evaluated in an applied situation (i.e., are decisions actually improved as a result of model implementation, and to what extent). Some reasons for this include; determining whether decisions are considered successful or not can take a long time to comprehend (i.e., understanding whether a player is worth what the organisation has paid/given up can take many years) (Massey & Thaler, 2013). Also, model evaluation should be assessed based on its performance to support decisions beyond the decisions which would have been made if the decision support model did not exist (Maymin, 2017). As such, evaluations of model success often have to rely on back testing, whereby the model can be used to determine if previous decisions could have been improved had the model been in place. However, this is often not practical in an applied setting, as it renders both data availability and analysis problems (Maymin, 2017). Specifically, back testing should not test model performance on the same data in which it was trained on; thus meaning that the amount of data available for training a model is reduced. Further, when back testing on potential alternative recruiting and contracting decisions, there is no definitive way to retrospectively determine what other clubs would have been willing to trade for a player/draft pick, or what remuneration a player would accept, respectively (Maymin, 2017). As such, producing accurate retrospective comparisons to hypothetical changes becomes increasingly difficult. Though this is the case for evaluating decisions which have longer term outcome responses, ideally decision support systems with shorter and more defined outcome responses would be developed with the intent for the system to validate itself. Various examples of this exist within other industries, such as process control, or decision analysis in medicine (Altman, Vergouwe, Royston & Moons, 2009; Wagholikar, Sundararajan & Deshpande, 2012).

In a complex and dynamic invasion team sport like AF, it is important for decision makers to understand that even the most complex model based on an extensive dataset can still have difficulty accounting for all the erratic contextual factors that exist (Hutchins, 2016). Some examples of these tangible factors include the consistency of a player's role over the course of a match, existing injuries and illnesses, as well as the mindset of a player.

The abovementioned difficulties in evaluating the effectiveness of objective models reflects the notions outlined by Alamar and Mehrotra (2011) and Rein and Memmert (2016) at the beginning of this thesis; there are still many common misunderstandings relating to a data driven focus towards supporting decisions. Without straightforward approaches to accurately determine the effectiveness of decision support models beyond that of the organisations current practices, there will likely be ongoing scepticism around what objective support decision makers should consider, and to what extent should their decisions be influenced by objective support (Alamar, 2013). Despite this, the notion that subjective analyses based on human expertise almost never makes more accurate decisions compared to objective analyses based on data in the long term, has been well documented in the notational literature of other disciplines (Ayres, 2008; Martin, Quinn, Ruger & Kim, 2004; Norman, 1993).

The remainder of this subsection of the general discussion will serve as an extended discussion of chapters three through six. Due to the inability to determine objectively quantifiable outcomes that emanate directly from player actions in AF, there is great difficulty in the ability to validate the models within this study using alternate study designs. With the advance in objective technologies, such as player tracking, and increased collection of tactical performance indicators, there looms an ability to create a more detailed representation of the specific equity of particular player actions. As such, there is the potential that the AFL Player Ratings, as well as other objective player performance metrics, will continue to be improved as a measure of objective player performance. As these metrics improves, there will be opportunities for the methods in the thesis to be rigorously validated with a potentially more robust player performance metric.

A decision tree analysis was conducted in both chapters four and six. Besides its suitability as an analysis tool, this specific type of model was conducted primarily due to their ease of visual interpretation, making them practical for use in an applied setting. In both these chapters a relatively basic explanation of the hyper-parameter tuning was outlined due to the emphasis of the studies being on the applied usability of the models. A more granular explanation is as follows; the model complexity parameters and minimum splitting were trialled and tuned using different combinations of parameters. In chapter four, this was conducted whilst also considering the 10-fold cross-validation performance of the model. In chapter six, this was conducted whilst considering the performance of the model on the test set. The combinations chosen for each study were those which retained a comparatively high classification accuracy, and smaller gap in performance comparative to other parameter combinations.

In chapter six, a descriptive analysis and visualisation of the IFPR and AFL Player Ratings was created as a practical application to assess the difference in evaluation between the subjective and objective systems, respectively. This descriptive analysis was outlined by indicating the amount of standard deviation between each player's season mean rating, as compared to the overall sample mean for each rating system. This method of comparison was conducted to counter the differences seen between the ratings systems, due to being on different scales with different dispersions.

Also in chapter six, the IFPR were used as the subjective measure of player performance. These ratings were completed by a single AFL accredited journalist for each match. Ideally we would have used either coaches or scouts ratings as the subjective measure of player performance in this study. However, a primary aspect of the analysis of this study was having a subjective rating on every player, for every round throughout the season. Unfortunately, within the AFL system there are no current subjective ratings which are both publicly available for use, and are conducted on all players (i.e., the AFL Coaches Association only attribute votes to five players per match, and the Charles Brownlow Medal only attribute votes to three players per match). As such, this study put an emphasis on the methodology, and how applications of the methodologies and models created as part of this study have the potential to be used in an applied setting (i.e., in a club setting which has access to both subjective and objective ratings on all players/potential draftees).

7.2 Industry Implementation

In addition to stakeholder buy-in, there is a technical component to the implementation of objective decision support systems in professional sporting organisations. For example, there is often a requirement for additional software, as well as practitioners/consultants with the ability to optimally design, implement and maintain aspects of the support system such as the user experience interface and data backend. Where possible, implementation of decision support systems into a professional setting would follow a framework. Though no specific research exists in the team sport literature outlining an overarching framework for the integration of decision support systems into professional sporting organisations, various similarities can be drawn from frameworks outlined in other industry organisations, such as small-and-medium businesses (Arnott, 2006; Blackwell, Shehab & Kay, 2006). Some translatable steps include:

- Identifying the specific organisational problems.
- Establishing whether integrated decision support systems can aid to improve the outcomes of the problems.
- Developing a team that consists of those individuals most capable of carrying out the projects successfully.
- Accessing appropriate software and available information sources.
- Educating decision makers and other users.

- Establishing the ideal level of integration.
- Purchasing or developing a system that is suitable for integration within the organisation.
- Revision and maintenance of the system post integration.

Various elements within the development and maintenance of a support system are integral for optimising the conclusions produced by applications. From a technical perspective this includes the data handling and modelling processes, such as data warehousing, handling of missing data, and the use of appropriate analysis methodologies (Liu, Li & Zou, 2016). In addition to ensuring the data are accurate, it is important to ensure the research applications are also translatable. This includes two main facets. Firstly, the applications must be interpretable. Can the research be interpreted in a practical and meaningful way by key decision makers? Do the key decision makers fully understand what the applications are implying, and how they should be used to improve their decision-making process? Secondly, the applications must be compatible. Are the findings useful, and can they be implemented within the current processes of the organisation? Each of these aspects is critical to ensure the conclusions drawn by the decision maker are not misleading (Hutchins, 2016).

In the following section, some specific examples are outlined of how the models produced in Chapters Four, Five and Six could be adapted and reproduced to support specific questions that AFL organisations face. The models outlined in these examples have not been adapted from the original studies to include additional seasons of data, and thus are only specific to data from each separate study.

7.2.1 Case Study – Macro level: Paul Puopolo

The outcomes reached in Chapter Six support the notion that overall player performance evaluations should consider both subjective and objective assessments in a complementary manner in order to accurately evaluate player performance. It is also reiterated that having an understanding of the differences between subjective and objective evaluations is of particular value to professional organisations. Across the 2013-2017 seasons, Paul Puopolo was consistently rated substantially different by subjective and objective performance evaluations (outlined by the IFPR and the AFL Player Ratings systems). Table 6.4 and Figure 6.7 outline a descriptive analysis and visualisation, respectively, of the player's average season ratings in comparison to the distribution of all player's average ratings across the 2013-2017 AFL seasons. Specifically, it outlines that the player was rated considerably higher by the objective ratings system, in comparison to that of the subjective system.

This example was chosen as it is representative of instances that occur both within professional AF, and other team-based sports. It also reiterates why overall player performance evaluations should consider both subjective and objective assessments in a complementary manner. These types of inconsistencies should be of particular interest to professional sporting organisations, and should raise various questions. Specifically, does the subjective rater/s have a bias against a particular player? One way to get an indication of this would be to utilise the explanatory model outlined in study four (Chapter Six) to identify whether the player's performances differ somewhat to what would be expected for other General Forwards. Using the classification tree model specific to General Forwards (Appendix C.2), the player's model expected IFPR can be outlined from their match performance indicators. As the model was trained on the data from the 2013-2016 seasons, the 2017 season was used in this example as it was appropriate for testing. Table 7.1 outlines both the actual and model-expected ratings across the 2017 season, and indicates that across the season the player was rated four less points than expected, which would raise their season average IFPR from 4.13 to 4.40 (from 0.56 SD below them mean, to 0.34 SD below them mean). This agreement between the actual and model-expected ratings indicates that alone it is unlikely the rater/s were overly biased with respect to the player.

Table 7.1 Actual and model-expected Inside Football Player Ratings across the 2017 season.

Round	Actual IFPR	Model-expected IFPR	Differential
1	6	5	-1
2	6	6	0
3	1	3	2
4	2	2	0
5	6	6	0
6	3	3	0
7	2	3	1
8	4	6	2
9	6	6	0
10	4	4	0
11	1	3	2
12	3	3	0
14	6	5	-1
22	5	4	-1
23	7	7	0
Total	62	66	4

Some secondary questions to this inconsistency would be; does the player's role actually most resemble that of a General Forward? If so, is this discrepancy seen with other General

Forwards? Does the AFL Player Ratings typically over-rate General Forwards? Alternatively, does/do the rater/s of the IFPR typically under-rate General Forwards? By utilising the performance profiles outlined in Chapter Four of this thesis, and the model presented in Figure 4.2, we can confirm (only for the 2016 season) that the player's role is most similar to that of a General Forward. As such, Figure 7.1 again outlines the player's average season ratings, however, now indicates the mean ± one standard deviation for all General Forwards (as opposed to all player). This visual outlines that General Forwards are on average rated lower by the IFPR, in comparison to that of the distribution for all positions.

Though this may somewhat account for the discrepancy seen, each of the abovementioned models indicate that the player may be undervalued subjectively, and could hypothetically be a value recruit. Further models outlined in this theses could then be applied to get an additional objective perspective on the players performance, and to identify other players most similar to that of the player, in the case he is unattainable for recruitment.

Figures 7.2A and 7.2B utilise each of the models outlined in Chapter Five to visualise the player's actual past performance and future player-specific expected performance, as compared to their fixed effect estimate of performance, with respect to their age and experience, respectively. The black lines represent actual performance from 2014 to 2017 and then the player specific expectation (±90% PI) of performance from 2018 to 2021. Red/blue ribbons represent fixed effects estimates based on characteristics of same player. This application indicates that the player's performance has been above the benchmark level of performance, but within the 90% PI consistently across the 2014-2017 seasons, with respect to both models. It also indicates that the player's performance is expected to remain fairly consistent across the four forecasted seasons in both models.

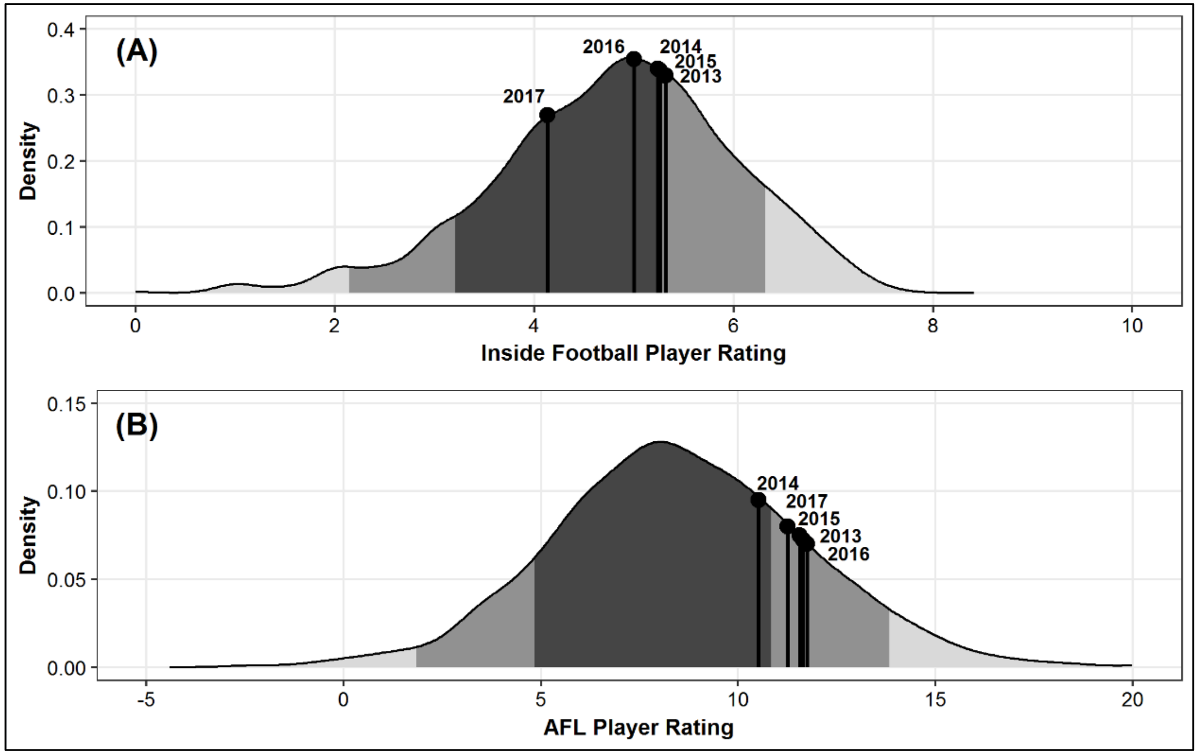

Figure 7.1 **Paul Puopolo's average season ratings in comparison to the distribution of all player's average ratings. (A) Inside Football Player Ratings and (B) AFL Player Ratings, across the 2013-2017 AFL seasons. Dark grey indicates mean ± SD for general forwards, medium grey indicates one to two SD for general forwards, and light grey indicates two plus SD for general forwards.**

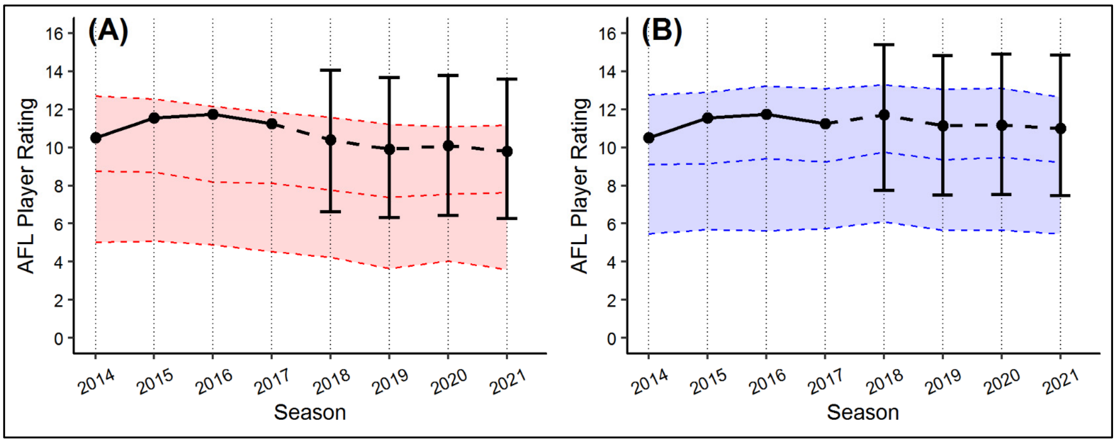

Figure 7.2 Benchmark levels of AFL Player Ratings for Paul Puopolo using (A) the age linear mixed model, and (B) the experience linear mixed model.

Further, Figure 7.3 outlines the network plot application outlined in Chapter Four, allowing for a visual representation of the inclusion of Paul Puopolo within the Western Bulldogs team network (for the 2016 season). Each player is connected with their three most similar players in the squad, as determined by the Euclidean distances. Players are coloured based on their role classification, and bubble size is a measure of each player's average absolute AFL Player Rating. The player of interest is highlighted with a larger black outline. This visual provides a clear indication of the player's similarity of that to other players within the team, and could provide support for key decision makers (i.e., coaches and team scouts) as to whether the inclusion of the player within the squad would be beneficial. Specifically, it may highlight that the player's role has the potential to fill a specific gap which exists, or has arisen on the clubs playing list (i.e., in the case of retiring players, or long term injuries). Conversely, it could indicate that the club already has similar suitable players within their list, emphasising that the inclusion of this player may potentially not be the best fit (or most pressing need) for the club.

Furthermore, in the instance where the player is a desired recruit, but is unattainable, Table 7.2 outlines the players most similar (during the 2016 season), using the player similarity model outlined in Chapter Four.

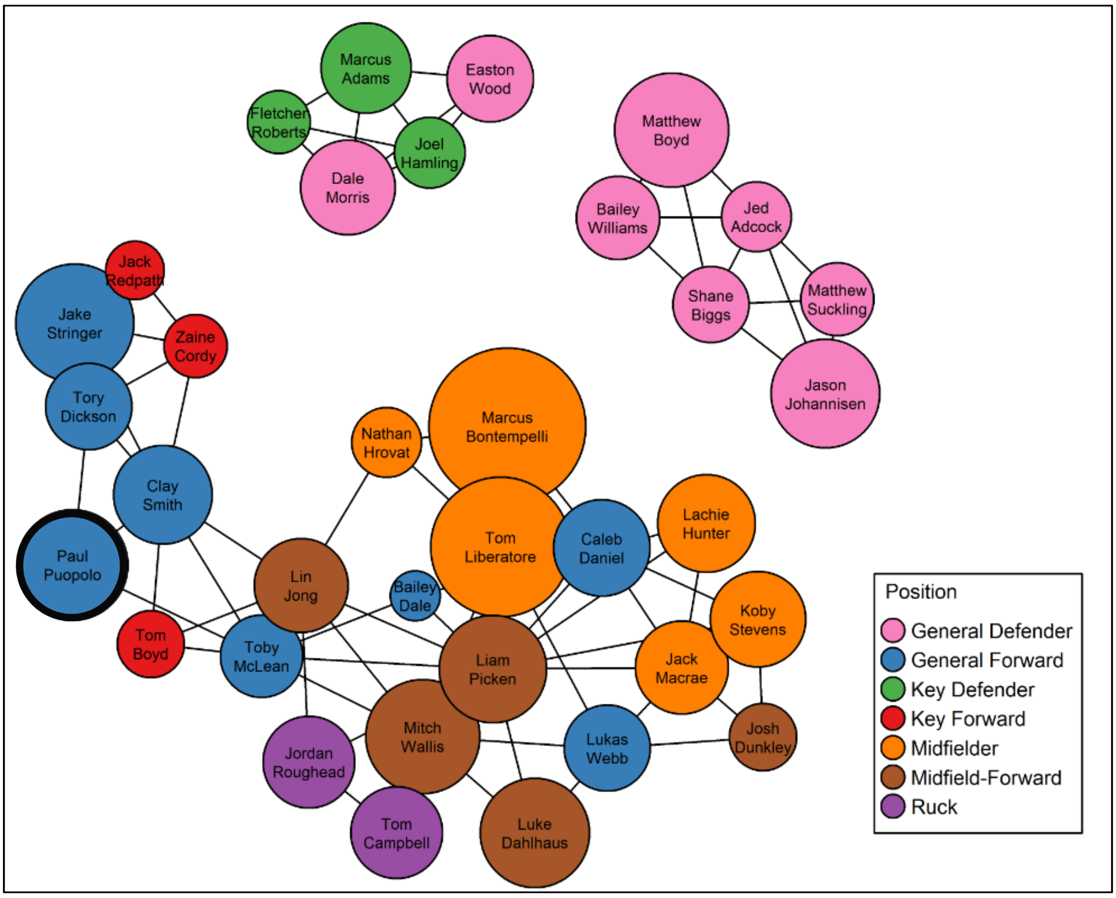

Figure 7.3 Network plot of the Western Bulldogs squad for the 2016 season, with the inclusion of Paul Puopolo.

Table 7.2 Dissimilarity measures of individuals with the five most similar playing roles to that of Paul Puopolo (General Forward, Hawthorn), during the 2016 AFL season.

Dissimilarity	Name	Player Role	Club
0.0848	Hayden Ballantyne	Gen Fwd	Fremantle
0.0882	Luke Breust	Gen Fwd	Hawthorn
0.0983	Chad Wingard	Gen Fwd	Port Adelaide
0.1019	Toby Greene	Gen Fwd	GWS Giants
0.1037	Michael Walters	Gen Fwd	Fremantle

7.2.2 Case Study – Micro level: Western Bulldogs (Round 19 2016)

In Round 19, 2016, the Western Bulldogs Football Club were required to replace five players who were injured during the previous week. In addition, they already had a further three players unavailable due to previous injuries. Figures 7.4A and 7.4B outline the network plot application produced in Chapter Four, which has been adjusted to represent the Western Bulldogs squad as at Round 19. Each player is linked to their three most similar players, and the bubble size is representative of the average AFL Player Ratings throughout the season to that point. In Figure 7.4A, the colour is representative of their positional role as determined in the supervised model of Chapter Four. In Figure 7.4B, the colour is representative of each players playing status prior to the match. As such, this application provides basic visual support for decision makers through a quantitative recommendation regarding the similarity of players within the team. Specifically, this application poses various levels of information for team selectors to support their decisions, including positional role, player similarity and a measure of player quality (seasonal average AFL Player Rating). For example, their thought process may be to replace Key Forward Jack Redpath with the only other alternative Key Forward Zaine Cordy.

However, this support application may evoke the notion of bringing in Jake Stringer as a suitable replacement, as he is one of Jack Redpath's three most similar players, and has shown to have a higher average performance rating across the first 18 rounds of the season.

7.3 Future Directions

There are various areas relating to modelling objective player performance data in AF which should be addressed in future work. Specifically, the AFL Player Ratings metric, as well as other new and existing objective player performance rating metrics should continue to be refined for use as quantitative measures of player performance in AF. As an example, the current AFL Player Ratings metric (and all other objective player performance models currently produced within the AFL) does not currently consider the field locations of teammates and opponents. As such, the current metrics, as well as new metrics should look to include further positioning dynamics, similar to that in other team sports (Gonçalves et al., 2017; Memmert et al., 2017). As additional parameters become factored into player performance rating metrics in AF, studies should look to focus on the continual development of decision support systems to improve our overall understanding of player performance and value, to assist with organisational decision-making. Further to this, the applications outlined from the objective player performance data as part of this thesis, could be adapted to use for additional tactical purposes.

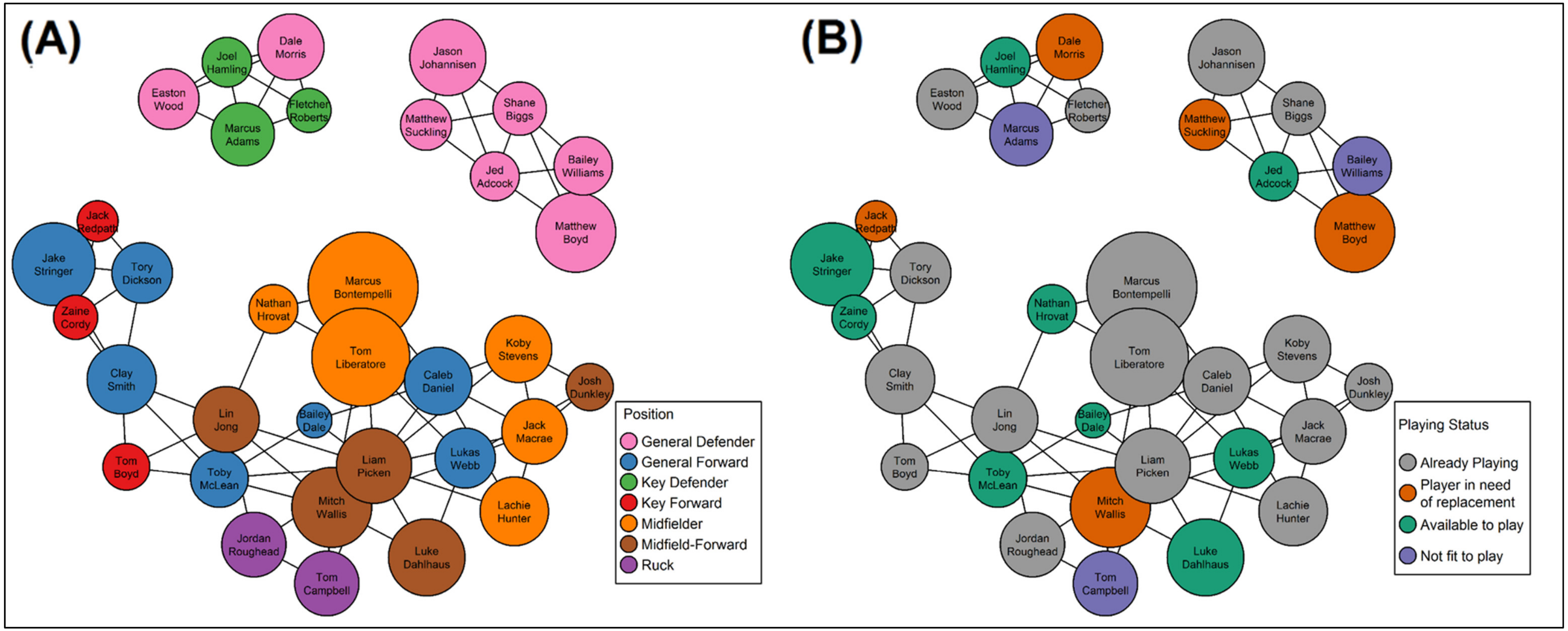

Figure 7.4 Network plots of the Western Bulldogs squad up until round 19 of the 2016 season. Players are connected with their three most similar players in the squad, as determined by the Euclidean distances.

Another area for future research should include comprehensive back testing and evaluations of organisational decisions to assess current decision-making processes; and to determine the extent to which decisions supported by objective models outperform decisions made merely by subjective considerations. In order to test the generalisability of the models proposed in this thesis, an external validation could revisit the methodologies with subsequent seasons of data to assess whether longitudinal variations exist. Additionally, for team sport decisions making tasks which have defined outcome responses, ongoing work should be conducted into the development of self-validating decision support systems allowing the implementation of systems to become a formalised process within professional sporting organisations.

7.4 Conclusions

The specific conclusions of this thesis are:

1. The construct validity of the AFL Player Ratings system is strong. This indicates that it is an appropriate quantitative measure of player performance for creating objective decision support applications for use within professional AFL organisations.
2. Player performance profiles outlined by the relative proportions of rating points acquired from each of the AFL Player Rating categories can accurately summarise individual player roles as well as similarity to other players within the AFL.
3. An individual's age, level of match experience, positional role classification and the characteristics of the draft in which they were first selected by an AFL club are all important factors to account for when assessing and predicting past and future player performances, respectively.

4. Assessing player performance for individuals with limited match opportunities at the AFL level might better be represented longitudinally by matches played, rather than age (which is traditionally used in team sport).
5. Where possible, player performance evaluations in professional sporting organisations should consider both subjective and objective assessments in a complementary manner to most accurately evaluate player performance.
6. Future work should focus on the development of objective decision support systems to provide unbiased support for decision-making task within professional sporting organisations.

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APPENDICES

APPENDIX A – APPROVAL TO CONDUCT RESEARCH

Appendix A.1 Victoria University Human Research Ethics Application Approval.

From: quest.noreply@vu.edu.au
To: Sam.Robertson@vu.edu.au
Cc: Sam McIntosh; Stephanie.Kovalchik@vu.edu.au
Subject: Quest Ethics Notification - Application Process Finalised - Application Approved
Date: Wednesday, 15 March 2017 2:00:43 PM

Dear DR SAMUEL ROBERTSON,

Your ethics application has been formally reviewed and finalised.

» Application ID: HRE17-014
» Chief Investigator: DR SAMUEL ROBERTSON
» Other Investigators: MR Sam McIntosh, DR STEPHANIE KOVALCHIK
» Application Title: Modelling player performance data for organisational decision support in professional Australian Rules football
» Form Version: 13-07

The application has been accepted and deemed to meet the requirements of the National Health and Medical Research Council (NHMRC) 'National Statement on Ethical Conduct in Human Research (2007)' by the Victoria University Human Research Ethics Committee. Approval has been granted for two (2) years from the approval date; 15/03/2017.

Continued approval of this research project by the Victoria University Human Research Ethics Committee (VUHREC) is conditional upon the provision of a report within 12 months of the above approval date or upon the completion of the project (if earlier). A report proforma may be downloaded from the Office for Research website at: http://research.vu.edu.au/hrec.php.

Please note that the Human Research Ethics Committee must be informed of the following: any changes to the approved research protocol, project timelines, any serious events or adverse and/or unforeseen events that may affect continued ethical acceptability of the project. In these unlikely events, researchers must immediately cease all data collection until the Committee has approved the changes. Researchers are also reminded of the need to notify the approving HREC of changes to personnel in research projects via a request for a minor amendment. It should also be noted that it is the Chief Investigators' responsibility to ensure the research project is conducted in line with the recommendations outlined in the National Health and Medical Research Council (NHMRC) 'National Statement on Ethical Conduct in Human Research (2007).'

On behalf of the Committee, I wish you all the best for the conduct of the project.

Secretary, Human Research Ethics Committee
Phone: 9919 4781 or 9919 4461
Email: researchethics@vu.edu.au

APPENDIX B – STUDY THREE SUPPLEMENTARY FIGURES

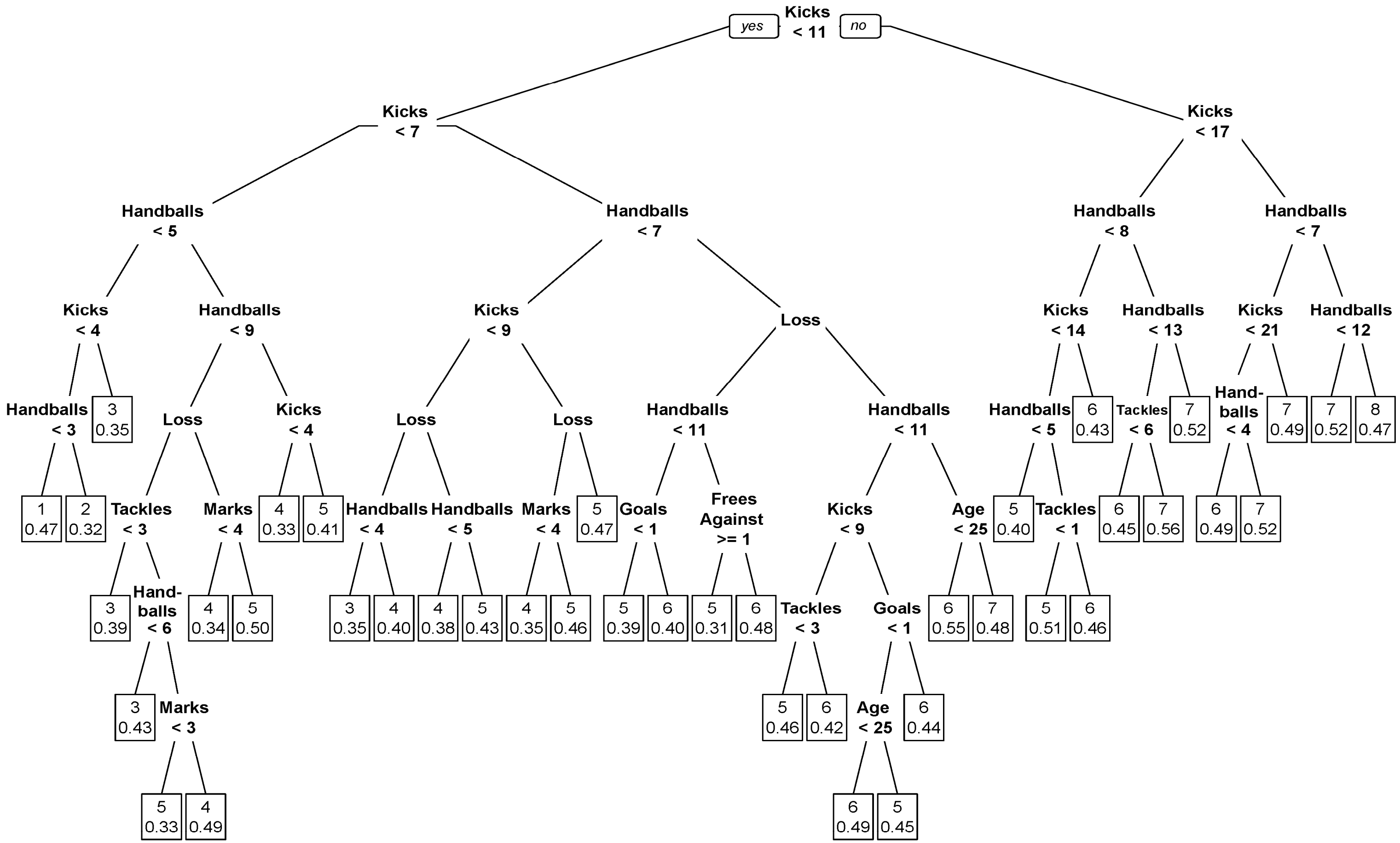
Appendix B.1 Descriptions of the seven positional roles used in this study.

Positional Roles	Description
General Defender	Plays a role on opposition small-medium forwards and usually helps create play from the backline
Key Defender	Plays on opposition key forwards with the primary role of nullifying his opponent
General Forward	Plays predominantly in the forward half of the ground but with more freedom than a key forward
Key Forward	Plays predominantly as a tall marking target in the forward line
Midfielder	Spends the majority of time playing on the ball or on the wing
Midfielder-Forward	Splits time equally between the forward line and the midfield. Often lines up on the half-forward flank but plays a significant amount of time in the midfield
Ruck	Has the primary role of competing for hit-outs at a stoppage

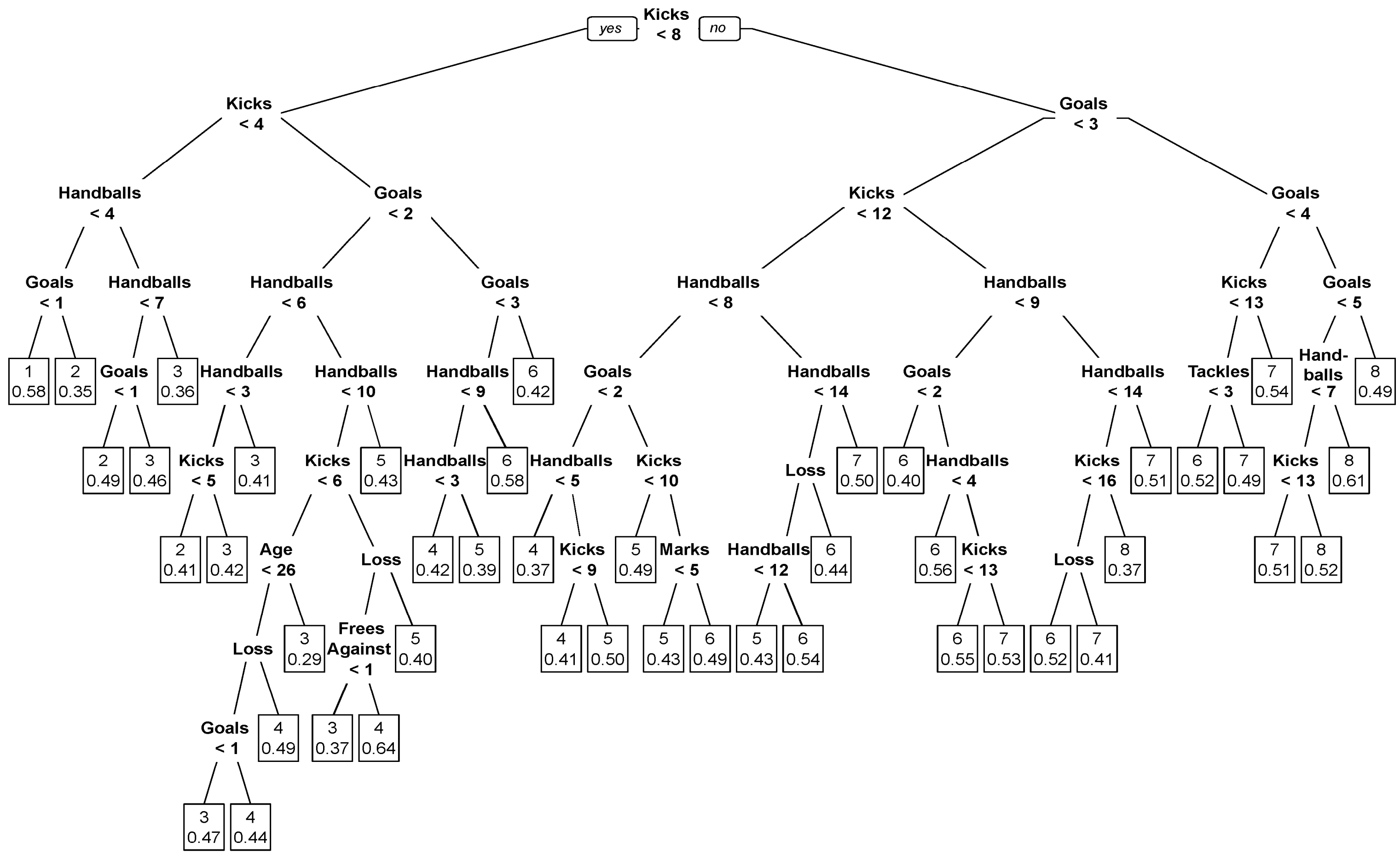
Appendix B.2 Descriptions of the three annual draft methods to enter an AFL list. In all three drafts clubs select players in the reverse order to which they finished on the final premiership ladder in the previous AFL season. To be eligible for selection, a player must be 18 years of age before the 31st of December following the national draft selection meeting.

Draft Type	Club Participation	Trading of Picks	Further Description
National Draft	Compulsory draft. Each club must exercise a minimum of three selections.	Picks can be traded between clubs.	Players selected by a club become ineligible to be included on the primary list of any other club for a period of two seasons. For the most part this draft consists of players finishing secondary school, who have been competing in elite junior feeder competitions.
Preseason Draft	Non-compulsory draft.	Picks cannot be traded between clubs.	Players selected by a club become ineligible to be included on the primary list of any other club for a period of two seasons. For the most part this draft consists of players who missed out on selection in the National Draft.
Rookie Draft	Non-compulsory draft.	Picks cannot be traded between clubs.	Players selected becomes part of the clubs rookie list, and cannot compete within the AFL until being promoted to the clubs primary list. For the most part this draft consists of players who missed out on selection in the National Draft or older players from second tier competitions.

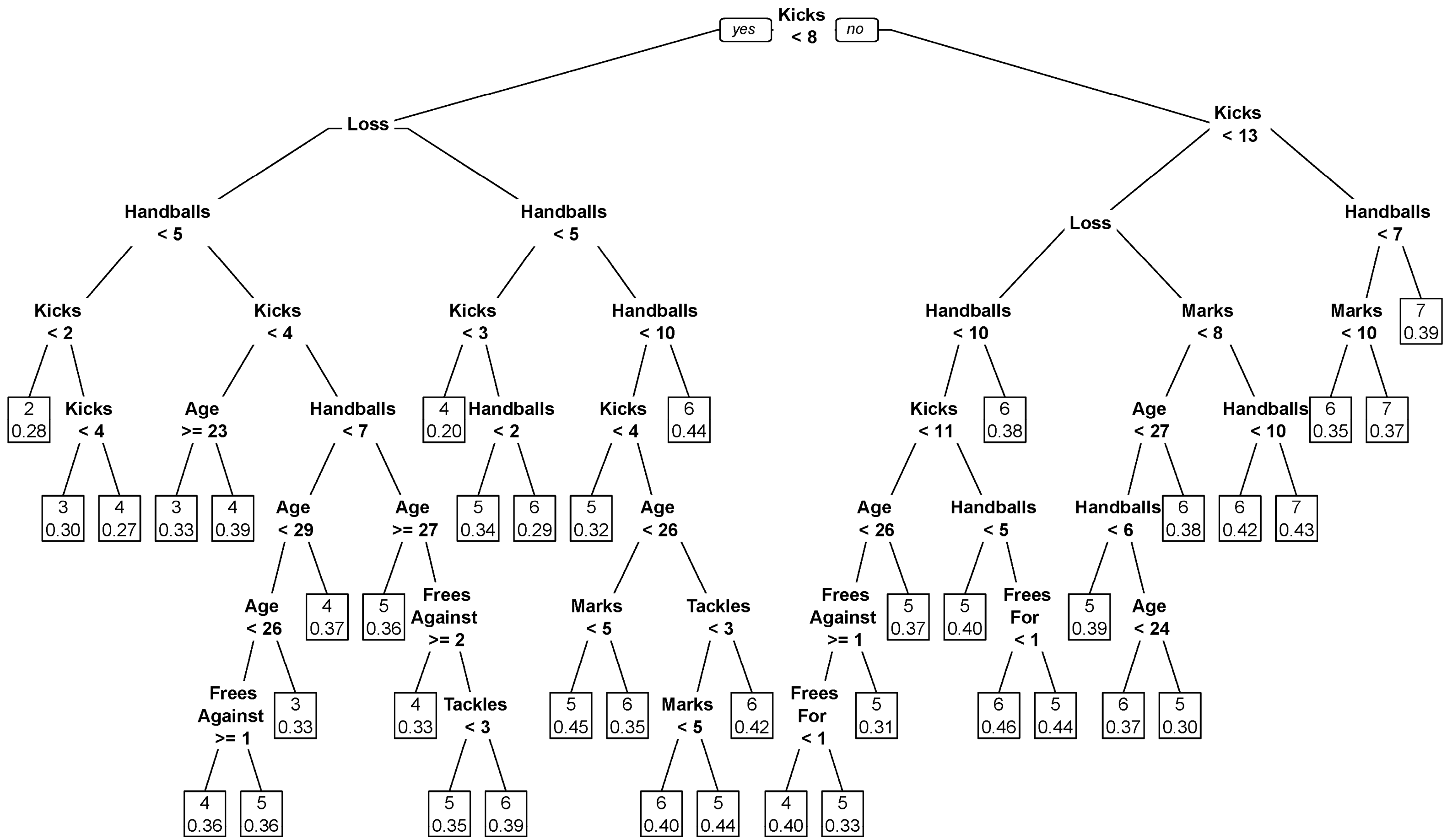
APPENDIX C – STUDY FOUR SUPPLEMENTARY FIGURES



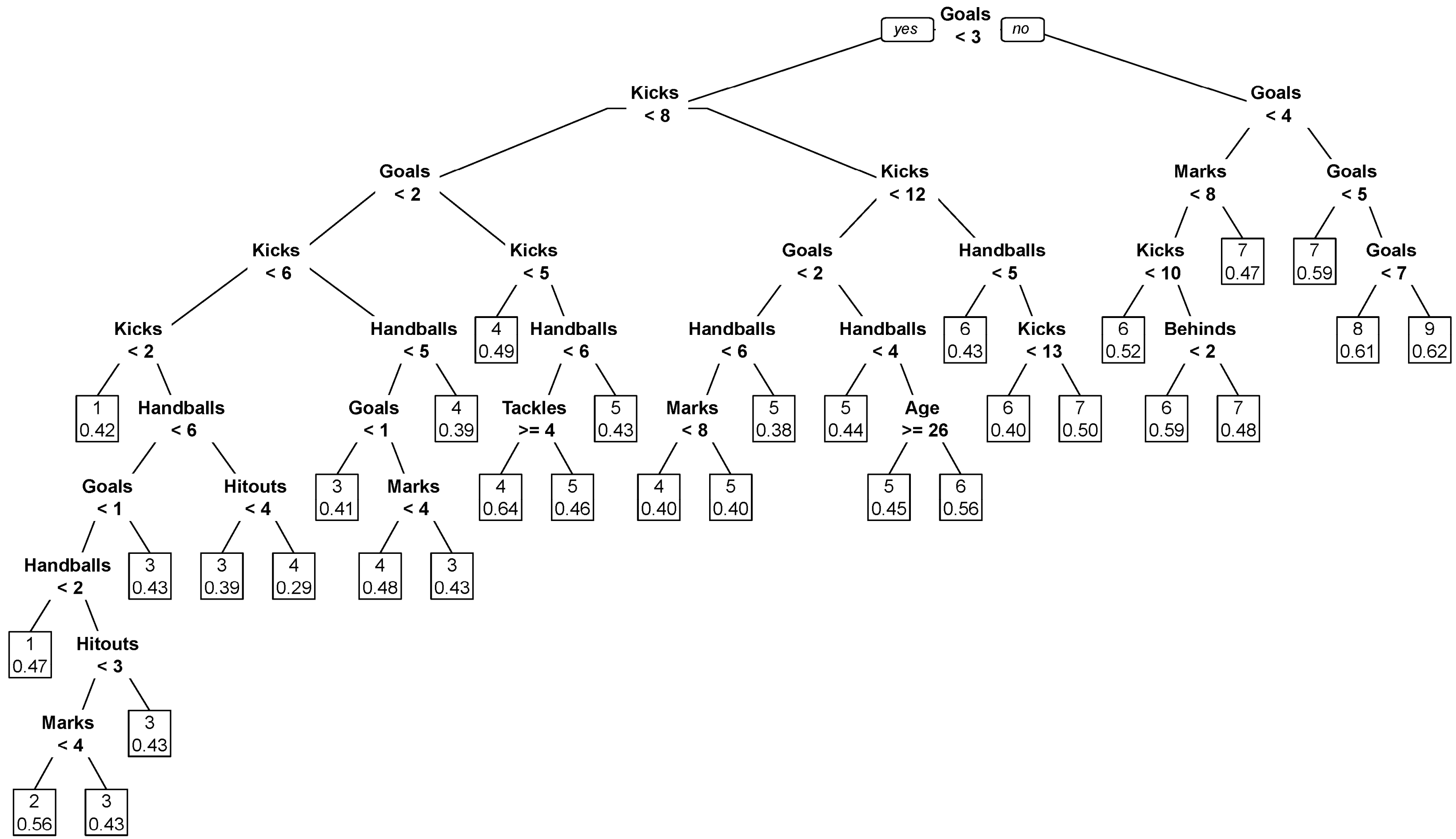
Appendix C.1 Classification tree model explaining Inside Football Player Ratings for General Defenders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.



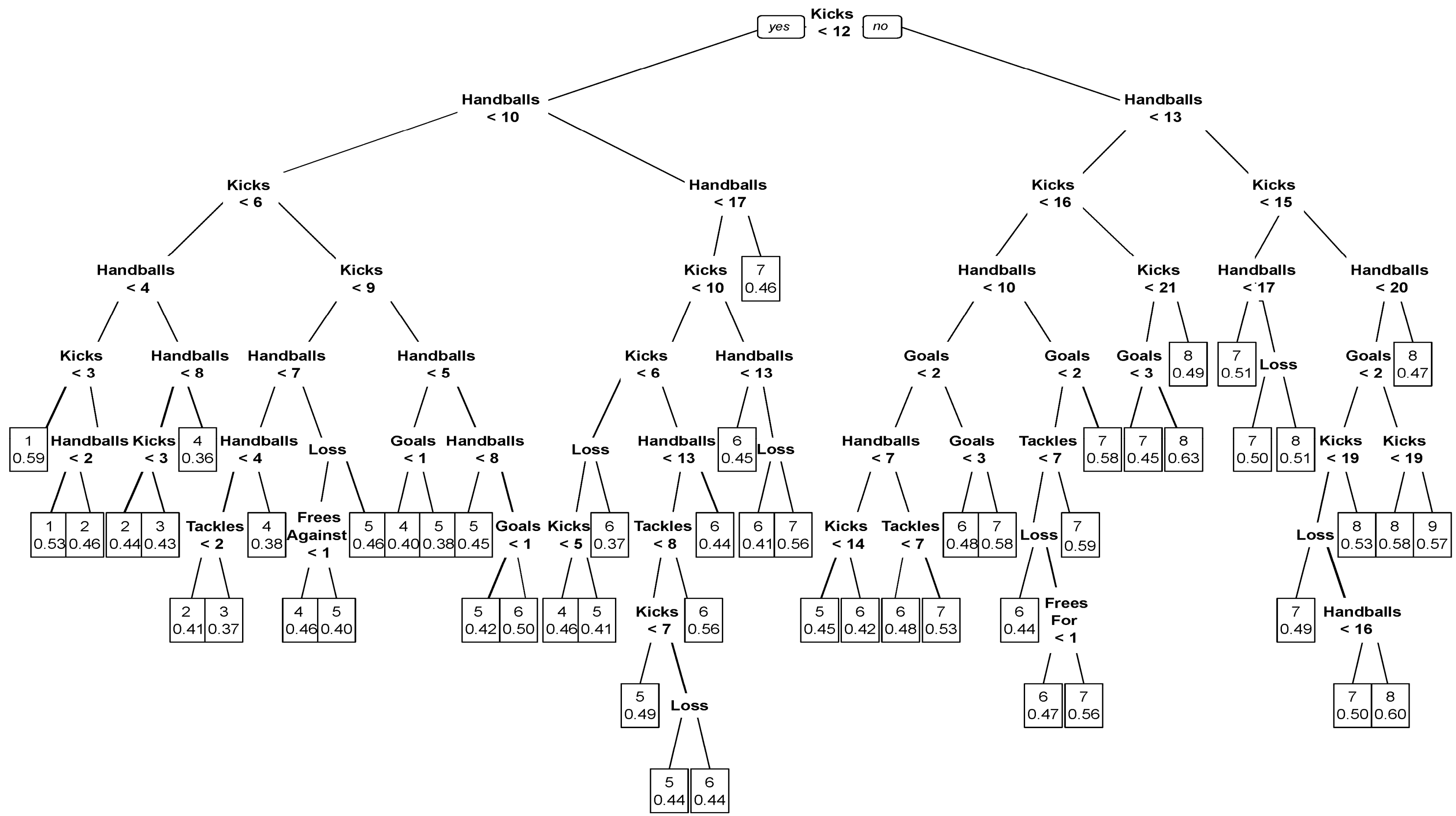
Appendix C.2 **Classification tree model explaining Inside Football Player Ratings for General Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**



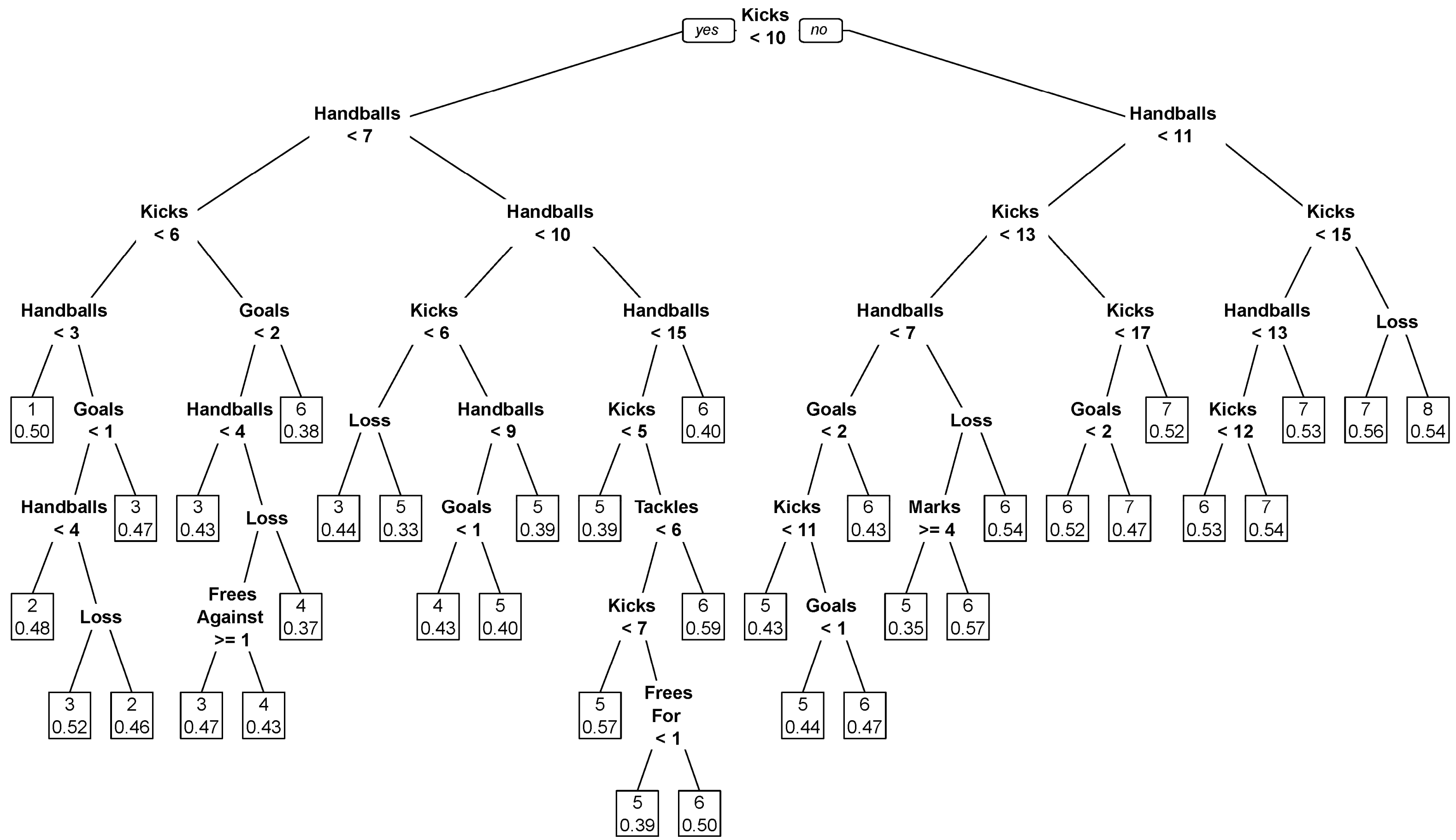
Appendix C.3 **Classification tree model explaining Inside Football Player Ratings for Key Defenders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**



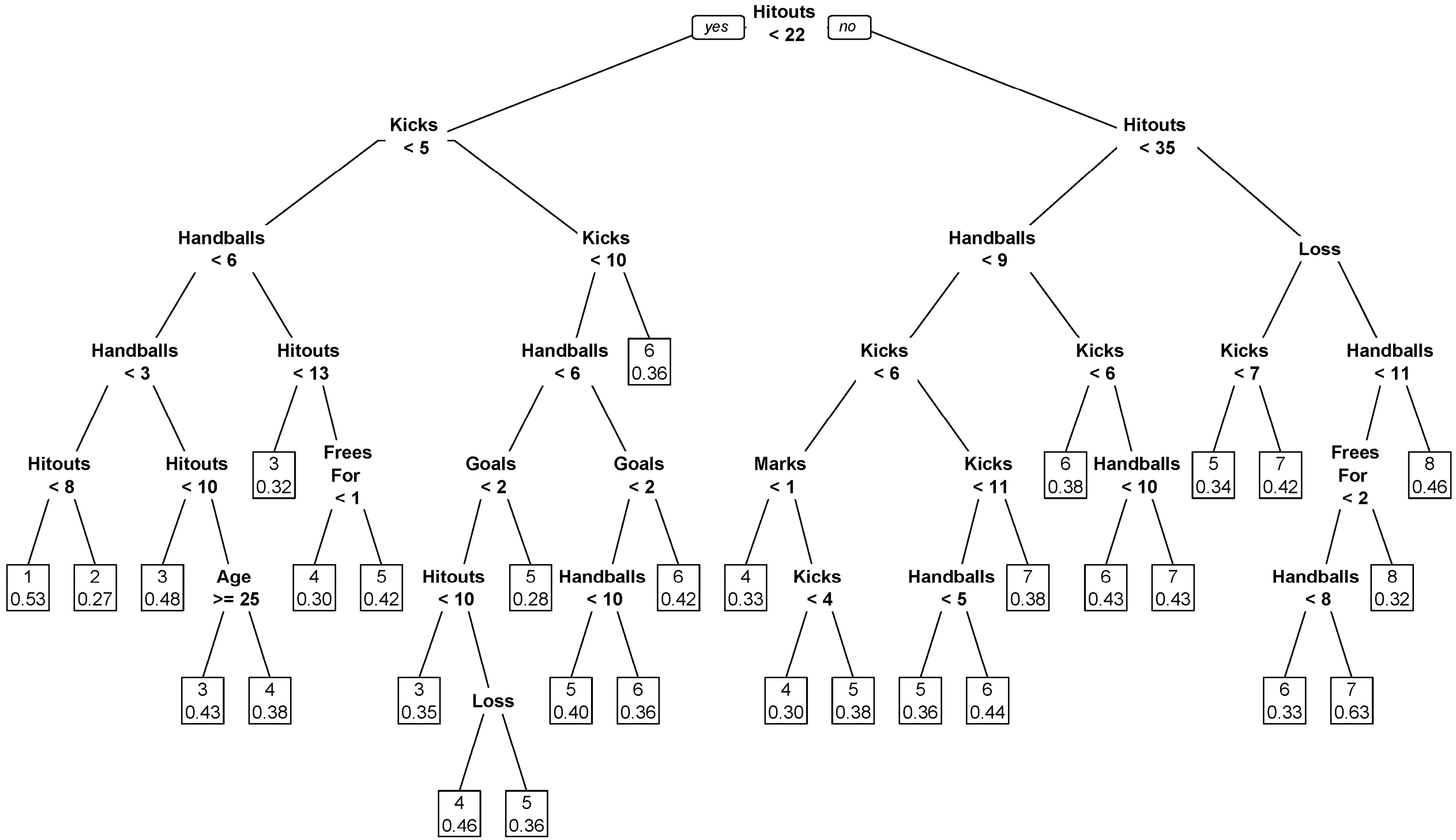
Appendix C.4 **Classification tree model explaining Inside Football Player Ratings for Key Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**



Appendix C.5 **Classification tree model explaining Inside Football Player Ratings for Midfielders from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**



Appendix C.6 **Classification tree model explaining Inside Football Player Ratings for Midfield-Forwards from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**



Appendix C.7 **Classification tree model explaining Inside Football Player Ratings for Rucks from match performance indicators. Terminal node variables outline the model-expected Inside Football Player Rating. Decimals indicate the absolute classification rate at the node.**