THE APPLICATION OF MACHINE LEARNING TO ENHANCE PERFORMANCE ANALYSIS IN AUSTRALIAN RULES FOOTBALL

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ABSTRACT

In this thesis, machine learning techniques are applied to enhance the development and implementation of methodologies in performance analysis. Ecological dynamics is used as a theoretical framework to underpin these methodologies. Australian Rules football is used as an exemplar to understand the influence and interaction of constraints on player and team dynamics. There is extensive theoretical research on the interaction of constraints in sport, however common analysis techniques have typically only explored one or two constraints and therefore do not fully reflect the complexity of the competition environment. To better understand the competition environment, the nexus of constraints must be considered in the analysis of sport. This thesis aims to address this gap. Firstly, this thesis explores how the use of ecological dynamics may aid the implementation of an interdisciplinary approach to sports performance research. These considerations are applied to Australian Football field and goal kicking, by exploring how multiple constraints interact and impact skilled performance, and how these differ between competition tiers. Furthermore, differences between analysis techniques are identified and aspects such as feasibility and interpretability are highlighted to facilitate an improved translation of research to the applied setting. Additionally, this analysis is furthered by exploring event sequences, determining not only the influence of multiple constraints around a disposal but also the preceding events. This thesis aims to advance the application of methodologies that explore multiple constraints and sequences of events, in order to enhance knowledge of the competition and training environments.

STUDENT'S DECLARATION

Doctor of Philosophy

"I, Peter Browne declare that the PhD thesis entitled

The application of machine learning to enhance performance analysis in 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: 21 December, 2020

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PUBLICATIONS ARISING DURING CANDIDATURE

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

1. **Browne, P. R**., Sweeting, A. J., Davids, K., & Robertson, S. (2019). Prevalence of interactions and influence of performance constraints on kick outcomes across Australian Football tiers: Implications for representative practice designs. Human movement science. (Chapter Four)
2. **Browne, P. R**., Sweeting, A. J., Woods, T. C., & Robertson, S. (2020). Applications of a working framework for the measurement of representative learning design in Australian football. PLOS ONE. doi:10.1371/journal.pone.0242336. (Chapter Six)

The following work has been published in peer reviewed journals during candidature but are outside the scope of this thesis:

1. **Browne, P.,** Morgan, S., Bahnisch, J., & Robertson, S. (2019). Discovering patterns of play in netball with network motifs and association rules. International Journal of Computer Science in Sport, 18(1), 64-79.

PRESENTATIONS ARISING DURING CANDIDATURE

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

1. **Browne, P.**, Sweeting, A., Davids, K., Robertson, S. (2019). Identifying the prevalence of interacting constraints and their influence on kick outcome in Australian Football: Implications for Representative Practice Designs. Presented at *9th World Congress of Science in Football (Preliminary work relating to Chapter Four)*
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2. Busch, A., Trounson, K., **Browne, P.,** Robertson, S. (2020). Effects of lower limb light-weight wearable resistance on running biomechanics. ePoster presentation at American College of Sports Medicine 67th Annual Meeting

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LIST OF SYMBOLS AND ABBREVIATIONS

⋃	and
=	equals
|	given that
>	greater than
=>	implies
<	less than
≤	less than or equal too
-	minus
%	percent
+	plus
±	plus or minus
P	P-value
AF	Australian Football
AFL	Australian Football League
AFLW	Australian Football League Women's
CBA	Classification Based on Associations rules
CI	Confidence Interval
CLA	Constraints-led approach
CV	Computer Vision
DSS	decision support system
e.g.	for example,
EPV	Expected Possession Value
FG%	Field Goal Percentage
GPS	Global Positioning Systems
i.e.,	in other words
ID	identification
iHeS	Institute for Health and Sport
LPS	Local Positioning Systems
m	metres
min	minutes
RLD	Representative Learning Design

RPE	Rate of Perceived Exertion
SE	Standard Error
secs	Seconds
SSG	Small Sided Game
STDX	Standardised X location
STDY	Standardised Y location
UWB	Ultra-Wide Band
WPA	Win Probability Added
xG	expected goals
xP	expected Points

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CHAPTER ONE - INTRODUCTION

Chapter Overview

This chapter outlines the background and objectives of the thesis (Section 1.1), offers an introduction to Australian Football (AF) to provide context for the analyses within the proceeding chapters (Section 1.2), and outlines the structure of this thesis (Section 1.3).

1.1 Thesis background and objectives

This thesis seeks to integrate key concepts from areas such as performance analysis and machine learning, and apply them under an ecological dynamics theoretical framework to Australian Football (AF).

1.1.1 Performance Analysis

Performance analysis is a sub-discipline of sport science, which aims to assess sport through objective data to inform practitioner decision-making (McGarry, 2009; O'Donoghue, 2009). Performance analysis can inform decision-making surrounding training design, player evaluation, team selection, team strategy and more (Painczyk, Hendricks, & Kraak, 2017). Athletic performance may be improved through planning and methodical training design, with the aim to improve physiological capacity and technical skills to a level which exceeds competition demands (Garganta, 2009). Recent advancements in sport technology have led to increasingly large quantities of data being collected in training and competition. Data, such as athlete field position, the frequency and accuracy of discrete skilled actions (e.g., passes and tackles), and physiological measures are now routinely collected in team sports (Couceiro, Dias, Araújo, & Davids, 2016). Whilst many aspects of data in sport are collected, a linear improvement in performance has not occurred which suggests current analysis techniques are not extracting complete meaning from the data (Couceiro et al., 2016). Additional insight could be gained from the available data with an increased application of machine learning techniques in performance analysis (McHale & Relton, 2018). The sub-discipline of performance analysis could also be furthered through the application of a theoretical framework to aid the integration and application of concepts and ideas from other disciplines (Clemente, Couceiro, Martins, & Mendes, 2013; Couceiro et al., 2016; Glazier, 2010).

1.1.2 Ecological Dynamics

Historically, performance analysis has not implemented a theoretical framework which underpins its methodologies (Balagué, Torrents, Hristovski, & Kelso, 2017; Glazier, 2010, 2017). A theoretical framework provides a foundation and rationale for the integration of ideas in research and industry applications. Ecological dynamics has been proposed as a framework to help enhance the field of performance analysis (Glazier, 2017; Vilar, Araújo, Davids, & Button, 2012) by integrating aspects of ecological psychology (Gibson, 1979), dynamical systems theory (Araújo, Davids, & Hristovski, 2006; K. M. Newell, 1986) and complexity science (Edelman & Gally, 2001). Importantly, it posits that performance outcomes and emergent properties of a system are a consequence of the coupled interaction between the individual and the environment (Araújo & Davids, 2011; Araújo et al., 2006). Scope exists for ecological dynamics to be implemented more completely in the applied setting and improvements are required to the application of ecological dynamics to provide meaningful and timely information about a player or team (Travassos, Davids, Araújo, & Esteves, 2013). Moreover, further applied research is required to demonstrate the capabilities of transferring this pedagogical approach into the applied setting.

In the applied setting, ecological dynamics can be used to design a representative environment through the exploration of constraints. Representative learning design (RLD) is a concept, derived from ecological dynamics and representative design, that helps to ensure experimental and practice tasks are representative of the competition environment (Brunswik, 1956; Pinder, Davids, Renshaw, & Araújo, 2011). An RLD can be created through the manipulation of constraints in training in order to mimic the competition environment (Davids, Button, & Bennett, 2008; K. M. Newell, 1986; Pinder et al., 2011). Constraints are typically classified in three categories: individual, task and environmental (K. M. Newell, 1986). A large body of research has been conducted in controlled or laboratory settings, which does not necessarily reflect the nature of the environment in which the tasks take place in the real-world (Farrow &

Robertson, 2017). Therefore, a more applied focus may facilitate the translation findings to the applied field (Farrow & Robertson, 2017).

There is extensive theoretical work on the interaction of constraints and how they influence each other in sport (Renshaw, Davids, Shuttleworth, & Chow, 2009; Ribeiro et al., 2019; Vilar, Araújo, Davids, & Button, 2012). However, there has been limited research of constraint interaction in the applied setting (see Robertson, Spencer, Back, and Farrow (2019) for exception). This is likely due to the limited control researchers can have over a sporting competition environment, paired with a historical focus on experimental design in a laboratory setting (Farrow & Robertson, 2017). Moreover, traditional analysis techniques which examine the influence of constraints are often linear in nature and adhere to a reductionist paradigm. These analysis techniques often only capture one or two constraints; however, sport is complex, and multiple constraints influence match events concurrently. Methodologies that account for the interaction of multiple constraints may better represent the whole picture surrounding competition environments. The collection and analysis of more variables, however, creates increased complexity in analytical modelling and can at some stage become impossible (Davids & Araújo, 2010). Machine learning offers techniques to help partially overcome this barrier and make complex data more feasible for analysis.

1.1.3 Machine Learning

Machine learning is a form of artificial intelligence which aims to uncover meaningful patterns within a dataset (Herold et al., 2019). In sport, machine learning has been used to evaluate expected point values (Cervone, D'Amour, Bornn, & Goldsberry, 2016), spatiotemporal trends (Gudmundsson & Horton, 2017) and to develop a greater understanding of athlete movement (Spencer, Jackson, & Robertson, 2019). Yet, machine learning has not been integrated in an interdisciplinary manner to its full potential in performance analysis. The application of machine learning techniques may aid in overcoming the aforementioned reductionist paradigm, as these techniques can help account for the complex and non-linear nature of sport. Machine learning can help make multivariate analysis more feasible, by understanding how constraints interact with one another to influence skilled performance. Thus, machine learning is used to improve the feasibility for the applied use of ecological dynamics in performance analysis.

1.1.4 Thesis Overview

In this thesis, the combination of an ecological dynamics theoretical framework and machine learning techniques are used to aid the development and implementation of methodologies in performance analysis. The exemplar of Australian Football (AF) is used. Firstly, this thesis explores how the fields of technology, analytics and perceptual science can encourage the use of ecological dynamics to implement an interdisciplinary approach to sports performance research (Chapter Three). Secondly, considerations from Chapter Three are applied to understand the influence of multiple constraints on AF field kicking performance, and this was measured and compared across competition tiers (Chapter Four). Thirdly, multiple analysis techniques are applied to consider how AF goal kicking is influenced by multiple constraints, whilst also demonstrating how varying analysis techniques can provide different outputs for the applied sport setting (Chapter Five). Finally, this thesis expands on the previously applied methodologies for a new application in the evaluation of the level of representativeness in an elite training environment, whilst accounting for the interaction of multiple constraints and sequences of events (Chapter Six).

1.2 Australian Football

Australian Football (AF) is an invasion-style sport which is played between two teams consisting of 22 players; 18 on-field players and four substitutes. Since its inception in the late

1850s it has evolved with continual changes to rules, gameplay and tactics (Braham & Small, 2018; Norton, Craig, & Olds, 1999; Woods, Robertson, & Collier, 2017). AF is a highly physical and skilled game (Gray & Jenkins, 2010). Over 500,000 people play AF worldwide, both men and women, however it is primarily played in Australia (Australian Football League, 2016a). It is predominantly played in outdoor stadiums, on an oval shaped field, with varying dimensions between 135 and 185 m in length and 110 and 155 m in width (Australian Football League, 2016b). In Australia, elite AF is played in a national league, the Australian Football League (AFL) and Australian Football League Women's (AFLW), at the state/territory level and in underage state/territory competitions (junior elite). Within the AFL, the regular season consists of 18 teams each playing 22 games plus finals (Sargent & Bedford, 2013).

The objective of an AF game is to score more points than the opposition. Scores consists of goals and behinds. A goal, worth six points, is scored by kicking an oval shaped ball through two upright middle posts at either end of the ground. A behind, worth one point, is scored by the ball going between the outer two posts. Scores for a game typically range between 50 to 150 points (Clarke, 2005). Games consist of four 20 min quarters, with extra time played each quarter for stoppages, and as such most quarters run for about 30 min (Australian Football League, 2016b; Gray & Jenkins, 2010). Teams swap directions of attack each quarter.

As in other invasion-style sports, a sequence of a critical events can lead to scoring opportunities (Nevill, Atkinson, Hughes, & Cooper, 2002). The ball is moved by three methods, kicking, handballing (holding ball in one hand and punching the ball with the other hand) or running with the ball. To dispose of the ball, players may kick or handball to another player and throwing the ball is illegal (Australian Football League, 2016b). AF is a contact sport, where players are able to tackle the opposition below the shoulders and above the knees when they are in possession of the ball (Australian Football League, 2016b). Similar to soccer, in AF effective kicking is a critical skill to maintain possession of the ball and this aided by the use of consistent and accurate technical skill executions (Bennett et al., 2018; Bonney, Berry, Ball, & Larkin, 2019; Cripps, Joyce, Woods, & Hopper, 2017). Effective kicking of the ball has been shown to be advantageous to a team's likelihood of success as it is the main method of moving the ball and only method to score a goal (Robertson, Back, & Bartlett, 2016).

Australian Football (AF) playing positions, in their simplest form, are broken down into forwards, midfielders and backs. A traditional field set up consists of: six forwards further broken down into three half forwards, a full forward and two forward pockets, six midfielders broken down into two wings and four followers/rovers, the backs are broken down into three half backs, a full back and two back pockets (see Figure 1.1) (Australian Football League, 2016b). Unlike other team invasion sports, play in AF is less structured and players are not confined to certain areas (i.e., compared to netball) or inhibited by an offside rule (i.e., compared to soccer and rugby). Due to this dynamic and freedom structure, athletes can perform a variety of roles across the entire field, which requires a certain physical profile alongside technical and tactical characteristics (Gray & Jenkins, 2010; Woods, Veale, Fransen, Robertson, & Collier, 2018).

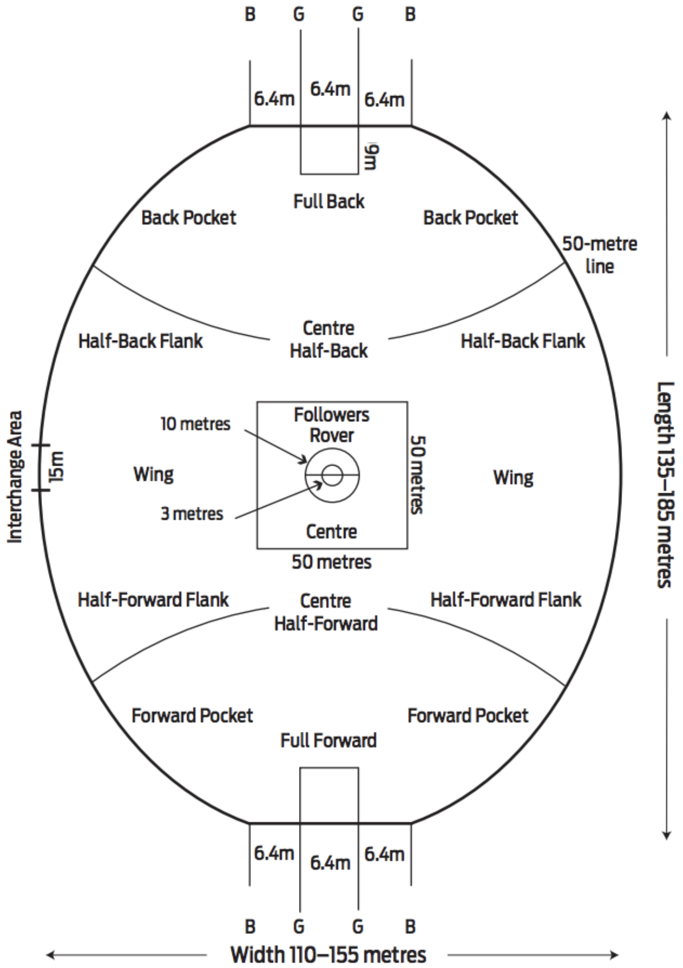

Figure 1.1. The dimensions, ground markings and playing positions of an AF ground. 'G' indicates goal post and 'B' indicates behind post. Australian Football League. (2016b). Laws of Australian Football. http://www.afl.com.au/afl-hq/afl-laws-of-the-game: Australian Football League

The AFL is a multi-billion dollar sports league which is continuing to grow (Gray & Jenkins, 2010). As a league, the AFL is heavily regulated to maintain competition equality. This is achieved through a reverse order draft, player salary cap and a football department 'soft cap'. This 'soft cap' limits what clubs can spend of within the football department, excluding player payments. Consequently, due to these regulations AFL teams must carefully consider the most efficient use of resources to lead to the best on-field performance. Therefore, clubs can gain a competitive advantage through innovation in sports science (Buttfield & Polglaze, 2016; Giblin, Tor, & Parrington, 2016). This thesis focusses on enhancing performance analysis methods through the use of machine learning techniques. This is to create improvements in methodologies to assess match performance and the multiple constraints which influence skilled output. This may enable a more objective analysis of player performance, and also inform training design to develop player technical and tactical characteristics. Improvements in training design may aid in increased transfer of training interventions to competition and improved match performance. Thus, providing multiple avenues to improve performance and develop a competitive advantage.

In this thesis, AF is used as an exemplar sport to demonstrate the applicability of ecological dynamics and machine learning techniques to aid the development and implementation of applied methodologies for the field of performance analysis.

1.3 Thesis Outline

Following this introductory chapter, this thesis contains an additional six chapters:

- Chapter Two provides a review of the relevant literature in both AF and broader team sports.
- Chapter Three is a narrative review exploring the literature with respect to the application of ecological dynamics and to encourage an interdisciplinary approach in sports performance research.
- Chapter Four applies the methodological considerations outlined in the narrative review surrounding constraints. It explores the differences in uni-, bi- and multivariate analysis approaches, in order to understand constraint interaction on field kicking in AF. This analysis is compared across different competition tiers.
- Chapter Five focuses on applying analysis techniques that aim to better model the interaction of constraints which influence goal kicking in AF. The feasibility of these techniques from an applied perspective is also considered.
- Chapter Six expands on the techniques used in the previous chapters and explores differences between training and competition environments. The differences between the interaction of constraints, their prevalence and the sequencing of events is measured between environments.
- Chapter Seven summarises the findings of the thesis and outlines the practical applications from each chapter. This final chapter outlines future directions to further understand constraint interactions in competition environments.

CHAPTER TWO - LITERATURE REVIEW

Chapter Overview

Chapter Two provides a summary of the literature related to the research contained in this thesis. This chapter contains sections outlining literature from performance analysis (Section 2.1), skill acquisition (Section 2.2), analysis techniques (Section 2.3) and conclusions (Section 2.4).

2.1 Performance Analysis

Sport is an integral part of health and entertainment in society (Gudmundsson & Horton, 2017). This literature review will focus on invasion-style sports unless otherwise stated. Invasion-style sports involve opposing teams competing for possession of an item (i.e., ball or puck). The playing area is constrained and teams aim to score whilst simultaneously preventing the opposition from scoring (Gudmundsson & Horton, 2017). The opposing teams have mutually exclusive aims, pursued at the same time, therefore resulting in many influencing interactions between both teams (Lames & McGarry, 2007). Examples of invasion-style sports include Australian Rules football (AF), European football (soccer), basketball, ice hockey, rugby, American football, and handball (Gudmundsson & Horton, 2017). The dynamic and ever-changing nature of sport makes analysis difficult. This is due to: i) the complexity which comes with individual player interaction, ii) that games are often formed of a random sequence of events, and iii) the sensitive nature of team and individual variables. This is further complicated by the numerous human and non-human components which act dynamically within a constantly changing competition environment (McLean, Salmon, Gorman, Read, & Solomon, 2017). The measurement of these interactions necessitates quantitative analysis.

Historically, the evaluation of team sport performance has been reliant on a coach's ability to recall critical, discrete actions from matches (Borrie, Jonsson, & Magnusson, 2002). Yet, it is not feasible for coaches to accurately recall the required information to provide a complete overview of performance (I. Franks & Miller, 1986). Therefore, sport scientists have attempted to use data to address this limitation to better understand performance and increase a team's chance of winning. Sport science is used to scientifically analyse and guide sport practice, with the aim of improving performance (Bishop, 2008; Coughlan, Mountifield, Sharpe, & Mara, 2019; Mellalieu, Trewartha, & Stokes, 2008). Sport science has historically centred on physiological and biomechanical factors, with little emphasis placed on the tactical behaviour of players and teams (Atkinson & Nevill, 2001; Garganta, 2009; McLean et al., 2019).

Accordingly, analysis could be expanded to evaluate how the technical, physical, cognitive and tactical aspects of performance interact with one another in training and competition to influence performance (Hughes & Franks, 2004; McLean et al., 2019). This complexity should be accounted for to better understand performance in research and applied settings.

Performance analysis is a sub-discipline of sports science (Carling, 2013; Glazier, 2010; Mackenzie & Cushion, 2013), alongside other sub-disciplines such as, physiology (Stølen, Chamari, Castagna, & Wisløff, 2005), biomechanics (Cust, Sweeting, Ball, & Robertson, 2019; Lees, Asai, Andersen, Nunome, & Sterzing, 2010) and sports medicine (Maffulli, Longo, Gougoulias, Caine, & Denaro, 2010). Performance analysis has been posited to help quantify the interaction of the constantly changing match and training environments. Many elite sporting clubs now employ full-time performance analysts within sport science departments to capture, analyse and evaluate sporting performance.

Performance analysis is a process of quantifying individual and team events and outcomes via systematic observation (McGarry, 2009). Performance analysts capture and analyse key information with the intent to improve performance. Traditional performance analysis has been described to have theoretical and practical aims (Lames & McGarry, 2007). The theoretical aim centres around understanding game structure, whereas the practical aims focus on the individual sporting processes (Lames & McGarry, 2007). Performance analysis has foundations in the manual recording of events in sport, however the methods and technology has developed over time (Gudmundsson & Horton, 2017).

Performance analysis has manually recorded events using human observation since the 1950s (Gudmundsson & Horton, 2017). However, the scientific research of match events has increased since the 1990s (Sarmento, Marcelino, et al., 2014). Human observation and manual methods can be time-consuming and are subject to human variation, which may result in poor efficiency and reliability (I. Franks & Miller, 1986; Gudmundsson & Horton, 2017). To improve reliability, data should be independent of the observer and therefore objective (Lames & McGarry, 2007). An increase in technology, and its application in the collection of match events and object trajectories, may improve objectivity and reliability of performance analysis (Cust, Sweeting, et al., 2019). However, the analysis and collection of these events could be further improved, as learnings from other disciplines could be applied to better generate insights into performance.

Notational analysis is a commonly used technique in performance analysis to analyse and describe events which are taking place within different phases of play (Vilar, Araújo, Davids, & Button, 2012). Notational analysis has foundational studies estimating distance travelled in basketball and American football in the 1930s (Messersmith & Corey, 1931; Messersmith & Fay, 1932) and the further influence of rule changes (Fay & Messersmith, 1938). It has been used to obtain indicators and counts of discrete actions and/or events (Gonçalves et al., 2019). Notational analysis typically records the *who* – *what* – *where* – *when* of match events, such as possessions, scoring or defensive actions (McGarry, 2009; Vilar, Araújo, Davids, & Button, 2012). However, understanding the *why* and *how* is also important to account for the unpredictable and complex nature of team sport (McGarry, 2009; Vilar, Araújo, Davids, & Button, 2012). The *why* and *how* can provide further context and insight to what is occurring, which may help provide important information for game analysis.

To understand the *how* and *why* of a match event, statistical analysis needs to account for the context surrounding events. A multivariate analysis approach broadly refers to analysis which considers multiple variables (Grimm & Yarnold, 1995), and can provide a better foundation for measuring performance compared with uni- and bi-variate techniques. This approach enables performance analysts to account for multiple variables and begin to provide more context and understand how variables interact (Rein & Memmert, 2016). This is necessary to provide feedback which can be accurately applied to help guide coach decision-making, training design and objectively analysing the sporting environment (McLean et al., 2019).

It has been suggested that a competitive advantage can be gained through performance analysis when applied with a theoretical underpinning (Balagué et al., 2017; Couceiro et al., 2016; Gerrard, 2016; Glazier, 2017). Currently, the application of a theoretical framework is not standard practice in performance analysis. However, performance analysis has the opportunity to grow as a sub-discipline, through the use of a theoretical framework and enhanced technical abilities, such as those found in analytics and technology. Theoretical frameworks such as ecological dynamics, complex systems and dynamical systems may aid the improvement and development of performance analysis. With improvements in technology, the ability to automatically capture and analyse games has increased, leading to the integration of performance analysis within the sport science field (Drust, 2010; Hewitt, Greenham, & Norton, 2016). Performance analysis needs to continue to evolve concurrently with technological developments and apply a theoretical framework to meet practitioner demands (Ramos, Lopes, & Araújo, 2018; Sarmento, Marcelino, et al., 2014).

As in many industries, the application of quantitative analysis in sport is growing (McHale & Relton, 2018). The combination of more accurate and increased data availability, alongside improved computational processing power, has led to more analysis within the sporting industry (McHale & Relton, 2018; Morgulev, Azar, & Lidor, 2018). In sport, match analysis has steadily increased with the availability of technology (Cust, Sweeting, et al., 2019; Sarmento et al., 2018). This has enabled statistics to become integrated within sport. Performance analysis has been used by key stakeholders to help aid informed decision-making surrounding player evaluation, team selection, training design and alteration of team strategy (McIntosh, Kovalchik, & Robertson, 2019; Painczyk et al., 2017). These decisions are underpinned by increased data quantity and quality as quantitative analysis in sport grows. Performance analysis may progress and improve data quantity, quality and analysis techniques by developing alongside other disciplines.

2.1.1 Interdisciplinarity

Interdisciplinarity advocates for experts across multiple disciplines to network, synthesise and integrate concepts and methods to generate and share new knowledge (Freedson, 2009; Piggott, Müller, Chivers, Papaluca, & Hoyne, 2019; Schary & Cardinal, 2015). Within sport science, a true interdisciplinary approach would see disciplines working collaboratively to fully encapsulate principles, concepts, data and methods to solve problems and enhance domain specific knowledge (Glazier, 2017). Independent theories, methodologies and measurement techniques from each discipline could be reconciled to build upon and learn from one another, which may reduce resource input and maximise information output. A Department of Methodology could underpin applied sport science to promote greater inter- and transdisciplinary in practice by removing siloed and insular thinking and avoid 'system capture' (Rothwell et al., 2020). Thus, interdisciplinarity affords collaborative problem-solving which may potentially lead to enhanced inquisition, the identification of new questions and the resolving of existing problems (Hristovski, Balagué, & Vázquez, 2014). For interdisciplinarity to occur new methods and procedures are required, which may challenge engrained and culturally pervasive disciplinary norms.

Interdisciplinarity may provide an alternate approach to aid the development of sport science. Interdisciplinarity is proposed as an approach which through uniting processes and procedures may aid in comprehending complex systems (Buekers et al., 2017). This could assist sport science, as sport science has been criticised for its insular nature, where sub-disciplines attempt to solve problems internally and do not share resources and methodologies (Balagué et al., 2017; Buekers et al., 2017; Burwitz, Moore, & Wilkinson, 1994; Davids, Handford, & Williams, 1994; Elliott, 1999). In research, this has manifested in the establishment and reproduction of sub-discipline specific methodologies and therefore redundencies as disciplines are using similar, yet separate, data and methodologies to understand performance (Cardinale, 2017; Glazier, 2017). In practice, this is often observed as the separation of departments in high-level sporting organisations, which may increase the level of isolated and siloed thinking (Otte, Davids, Millar, & Klatt, 2020; Rothwell et al., 2020). Accordingly, numerous proposals have been made for sport science to progress beyond these insular confines and embrace an inter- and even transdisciplinary approach have been made (Buekers et al., 2017; Burwitz et al., 1994; Button & Croft, 2017; Glazier, 2017; W. H. Newell, 2001; Piggott et al., 2019). Adoption of an interdisciplinary approach in sport is challenging, but would serve to coordinate and unify activity, communicate translatable ideas coherently with consistent visuals and terminology and design and quantify activities which lead to the emergence of complex and adaptive athlete behaviours (Balagué et al., 2017; Glazier, 2017; Piggott et al., 2019; Rothwell et al., 2020). Interdisciplinarity can be a method to promote integration between disciplines and help collaboration within sports science. This could enable research and applied problems to be addressed in a new and innovative manner. In research and practice the number of interdisciplinary publications is limited (Buekers et al., 2017; Piggott et al., 2019). Therefore, more research is required to better understand how interdisciplinarity can occur, the impact of interdisciplinarity, and how to apply interdisciplinary practices in the applied setting.

2.1.2 Data in Sport

Data can be used to understand sports performance; however, the analysis and methodologies that are applied are critical to understanding the data. Data in sport can contain information surrounding physical output, technical proficiency, team formations and more (Rein & Memmert, 2016). Within elite sport, tracking systems and companies specialising in sport specific data collection have made data and analytics more accessible for many sports.

A considerable amount of effort has gone into the development of technology to aid information gathering and enhancing understanding in sport (Couceiro et al., 2016; Miah, 2017). Large datasets have become more available in elite sport. This has presented opportunities in performance analysis to analyse team behaviours (Alexander, Spencer, Mara, & Robertson, 2018), measure the point value of a possession based on specific match context (Cervone, D'Amour, et al., 2016), and calculating ideal defensive movement patterns (Le, Carr, Yue, & Lucey, 2017). However, the performance output has not necessarily improved in a linear manner alongside this increase in data and analysis (Couceiro et al., 2016). A proposed reason for this is the lack of time, and the understanding and ability to present data in a useable format (Couceiro et al., 2016; Coutts, 2014; Fullagar, Harper, et al., 2019; Fullagar, McCall, Impellizzeri, Favero, & Coutts, 2019). To overcome these issues, improved data management, and the development of analytical skills and communication is required. The collaboration between sport science sub-disciplines and other fields, such as computer science, may aid with data management, analysis and communication (Balagué et al., 2017; Coutts, 2014; Glazier, 2017; Rothwell et al., 2020).

In the applied setting, the development of technology in sport has made the calculation of metrics more feasible. Metrics can be generic across several sports, such as passing efficiency, whilst others are sport specific, such as Field Goal percentage (FG%) in basketball. The exploration, generation and analysis of metrics is crucial to applying data to understand a team's or an individual's ability to perform under different circumstances. Metrics are commonly used in the applied setting as data enables the objective assessment of individual and team performance, thus reducing bias from subjective assessments (Coughlan et al., 2019; Painczyk et al., 2017). However, the uptake of information by practitioners has been limited due to inconsistency in sport science messaging and the availability of peer reviewed research (Couceiro et al., 2016; Fullagar, Harper, et al., 2019; Rothwell et al., 2020). Furthermore, the application of data and generation of metrics has not always accounted for the complex nature of sport. Little is known about how these different factors interact with one another to influence tactical behaviour (Rein & Memmert, 2016).

Sport consists of many different data types, a majority used in performance analysis can be classified under match events and object trajectories. Match events and object trajectories have been used separately and together to generate statistical insights into game play. For instance, understanding of how players interact with one another through passing network analysis can provide insights into player connectivity (Gyarmati & Anguera, 2015; Gyarmati, Kwak, & Rodriguez, 2014). Collective team behaviour (Alexander et al., 2018), frequency of events (Ireland et al., 2019), player load and physiology (Mallo & Navarro, 2008), amongst other measures of performance, can also be gathered through analysing match events and object trajectories (Le et al., 2017). These varying insights may allow for performance analysts to work with coaches, to better understand their own team's strength and weakness in tactics and strategy as well as that of their opposition (Almeida, Ferreira, & Volossovitch, 2014; Godbout & Bouthier, 1999; Taylor, Mellalieu, & James, 2005).

2.1.2.1 Match Events

Matches are comprised of a series of events which can be expressed discretely, in sequence or continuously. These events are referred to as match events (Stein et al., 2017). Match events consist of important moments and technical and tactical actions (Gudmundsson & Horton, 2017; Pérez-Ferreirós, Kalén, Gómez, & Rey, 2019). Match events traditionally include passes, shots and infringements. Match events are typically recorded using video analysis, manual notational analysis or automated event detection (Stein et al., 2017). Match events can be recorded at a player or team level, giving insight into individual contribution or a team's tactics. They provide a method to evaluate performance over a range of time (Andrienko et al., 2017).

Match events can help understand trends in performance and provide insight into complex and dynamic environments. Match events can often be used as performance indicators. In AF, the frequency of match events and their influence on match outcome have been analysed

(Robertson, Back, et al., 2016). The number of inside 50s, marks and contested possession were the most important contributors to match outcome (Robertson, Back, et al., 2016). This may help inform coaches and allow for more effective training design and game plans (P. Jones, James, & Mellalieu, 2004). In rugby tackle location has been used to predict likelihood of a scoring (Kempton, Kennedy, & Coutts, 2016). This information in rugby can begin to inform players and coaches into the ideal length of offensive play and whether further defensive action needs to take place, given the context of the situation (Kempton et al., 2016). These traditional statistics have been used to provide an overview of a game or to help determine the best player or identify a replacement or similar player (Gyarmati et al., 2014; Peña & Navarro, 2015), or to determine overall patterns in game style and tactics (Spencer, Morgan, Zeleznikow, & Robertson, 2016). The appropriate selection of match events is important in defining and measuring performance (Castellano, Casamichana, & Lago, 2012). It is also important that the number of games analysed is taken into account, and additionally, how findings change between and within teams and across time (Pérez-Ferreirós et al., 2019).

Analysis should include context to help measure performance accurately. Performance can be determined by understanding how trade-offs between different match events may alter the likelihood of scoring (O'Shaughnessy, 2006). In AF the development of an equity metric enabled the possession value to be determined for the location of the possession (K. Jackson, 2008; O'Shaughnessy, 2006). Improvements in understanding sport could be enhanced by accounting for more context such as time, location and the constraints surrounding an event. Additionally, match events paired with equity values can provide further insight into the quantification of an individual's performance (K. Jackson, 2008). This information could lead to new metrics and methodologies which could inform coaches of contextual and constraint interaction and influence of their own team. Furthermore, this could also offer insight into how other teams cope in similar situations, or whether their tactics differ (Hobbs, Gorman, Morgan, Mooney, & Freeston, 2018).

Game style can begin to be determined and measured using match events. Passing patterns in soccer have been analysed using flow motifs and network theory (Gyarmati et al., 2014; Peña & Navarro, 2015). Barcelona FC, who were the most successful team based on wins in the Spanish league 2012/2013 season, were found to have a unique passing pattern compared to their opposition (Gyarmati et al., 2014). Conversely, a different study found teams with an increased number of ball movement strategies, i.e., variable passing patterns, compared to their opposition created more scoring opportunities (Peña & Touchette, 2012). Thus, a unique passing style and variable passing patterns have both been found to be successful, indicating more is at play than simply the passing style of team in its use as a performance indicator. Other factors such as the influence of opposition could provide more insight. For example, in basketball, shooting trends for individual players have been quantified, then compared to how these trends changed against different defenders (A. Franks, Miller, Bornn, & Goldsberry, 2015a). Defenders had a varying effect on offensive output (A. Franks et al., 2015a). This begins to create an understanding to how defence can influence offence and performance.

Historically, many measures of performance have isolated just one aspect of the game. Multivariate analysis techniques could progress this type of analysis by helping to account for the context within these complex systems. One multivariate approach which can be applied to understand passing patterns and the context in which they occur, is association rules. Association rules have been used to discover preferred passing patterns and outcomes in invasion sports (Browne, Morgan, Bahnisch, & Robertson, 2019; S. Morgan, 2011; Stöckl & Morgan, 2013). They have also been used to understand how constraints interact to influence match events in AF (Robertson et al., 2019). The benefit of this approach is that both the passing patterns and context around passes could be included within a single analysis. This may account for some context, such as opposition pressure and time in possession, which is influencing the success of the passing strategy. Hence, a multivariate approach can help the analysis of match events to measure performance, however this could be furthered by exploring spatiotemporal trends.

Metrics which use match events are typically not spatially or temporally informed, and hence do not provide the complete context around what is being measured (Gudmundsson & Horton, 2017). However, when match events are combined with specific pitch locations, further tactical information can be extrapolated from the data (Bradley, O'Donoghue, Wooster, & Tordoff, 2007). Additionally, as match events have differing levels of importance at different stages of a game, another aspect of match events which could be explored further is the temporal relationships between match events (Borrie et al., 2002). For instance, the value of an assist, which occurs immediately before a goal, is potentially more influential than an assist which occurs ten seconds before a goal. This may occur as the importance of the pass assisting the goal potentially reduces as the time gap between the two events increases. In a match specific context, such as a close game, different match events become more important, such as fouls and foul shots in basketball (Ibáñez et al., 2008; Kozar, Vaughn, Whitfield, Lord, & Dye, 1994). These relationships also exist within AF, and the influence of match events and their timing have been used to calculate the match equity (O'Shaughnessy, 2006). For instance, in AF winning possession of the ball whilst under physical pressure has been shown to be difficult to convert into a score, and win probability is heavily influenced by time remaining (O'Shaughnessy, 2006). Metrics used in sport are typically linear and reductionist in nature. The feasibility of undertaking such studies has been a major limitation in their application in research and industry. Yet, continual improvements to technology have enhanced the measurement of almost all aspects of sport and made this style of analysis achievable. It is important to continue development in this area as an improved understanding of game-related statistics and match events may allow for enhance sports performance research (Ibáñez et al., 2008).

2.1.2.2 Spatiotemporal Data

The analysis of spatiotemporal data and its subsequent communication can provide more context than aggregated match event data alone. Spatiotemporal data consists of the position of an athlete, object or event, measured over time (Gudmundsson & Horton, 2017). Spatiotemporal data is often categorised into two subsections: i) object trajectories, which capture the movement of players and/or the ball; and, ii) match events, which also include a record of location and time of instances (Gudmundsson & Horton, 2017). Analysis of these data types can occur at team (D'Amour, Cervone, Bornn, & Goldsberry, 2015; Mehrasa, Zhong, Tung, Bornn, & Mori, 2017) and individual levels (Bialkowski et al., 2014a, 2014b; Cervone, D'Amour, Bornn, & Goldsberry, 2014; Gyarmati et al., 2014; Peña & Navarro, 2015). Thus, spatiotemporal data can provide wide-ranging insights into sports performance.

The progress in tracking technology has made it possible to measure player location, and thus track athlete movements (Memmert, Lemmink, & Sampaio, 2017). Technological advancements such as Global Positioning Systems (GPS), Local Positioning Systems (LPS) and video-based tracking software, also known as computer vision, allow for the collection of spatiotemporal data (Andrienko et al., 2017; Aughey, 2011; Aughey & Falloon, 2008; Bialkowski et al., 2014a, 2014b). Position is typically recorded as x- and y- or longitude and latitude coordinates for the ball or an athlete's location over time. These systems can provide data which can be used to predict possession outcomes (Cervone, D'Amour, et al., 2016), player performance (Bruce, 2016), understanding player trajectories (Gudmundsson & Horton, 2017; Gudmundsson & Wolle, 2014) and collective behaviour (Alexander et al., 2018; Alexander, Spencer, Sweeting, Mara, & Robertson, 2019). Differences exist in the tools used to collect spatiotemporal data.

Tracking technologies use different tools to collect spatiotemporal data. Satellites are used in GPS (Aughey, 2011; Larsson, 2003), whereas LPS (Sweeting, 2017) and video-based software (Colyer, Evans, Cosker, & Salo, 2018) estimate position in relation to local coordinates of a playing space. Technology such as Radio-frequency (RF) and Ultra-Wide Band (UWB) are used to allow communication between LPS mobile nodes which are worn by athletes and anchor nodes positioned in specific locations around a playing area (Hedley et al., 2010). A major advantage of computer vision is the ability to track players without devices being worn by players. Typically, high definition cameras are mounted around the pitch or court and objects are tracked 10-25 times per second and are semi-automated, however the system is heavily dependent on camera set-up (Barris & Button, 2008; Gudmundsson & Wolle, 2014). Colour identification is another important consideration; if playing uniforms do not contrast with the court or are misread within court-placed sponsorship logos, data may be incorrectly recorded (Pers & Kovacic, 2000). Beyond object tracking, computer vision can allow for micro-actions, such as off-ball running, cut types, screens or blocks to be recorded (Sicilia, Pelechrinis, & Goldsberry, 2019). These actions are vital for competition performance, but rarely recorded due to technology limitations and feasibility (Sicilia et al., 2019). In AF, automated event detection could streamline the collection of match events such as kicks, handballs, tackles. This may allow for less personnel to be involved in the collection of these events, and those resources better used to analyse the events. As these technologies continue to improve, and performance analysis techniques also improve, the use of trajectory data will become more feasible. For in-depth reviews see Sarmento et al. (2018), Couceiro et al. (2016) and Ribeiro et al. (2019).

Since tracking technologies were introduced to sport, the 1990s for computer vision, and early 2000s for GPS, their precision and accuracy has improved (Aughey, 2011; Gudmundsson & Horton, 2017; Intille & Bobick, 1999; Sathyan, Shuttleworth, Hedley, & Davids, 2012). The validity of tracking technologies have been derived from various instruments including the trundle wheel (Edgecomb & Norton, 2006), computer vision (Aughey, 2011; Duffield, Reid, Baker, & Spratford, 2010) and other reference systems such as Vicon (©Vicon Motion Systems, Oxford Metrics, UK) (Hodder, Ball, & Serpiello, 2020). The accuracy of player tracking systems has been measured across a range of environments, courses, capture volumes and against varying criterions (Aughey, 2011; Frencken, Lemmink, & Delleman, 2010; Hodder et al., 2020; Linke, Link, & Lames, 2018; Mara, Morgan, Pumpa, & Thompson, 2017). Testing design has a large impact on GPS validity and reliability, for instance if an athlete is travelling at a slower pace and in a straight line, the validity and reliability is improved (Castellano, Casamichana, Calleja-González, San Román, & Ostojic, 2011; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010; R. J. Johnston, Watsford, Kelly, Pine, & Spurrs, 2014; Varley, Fairweather, & Aughey, 2012). Tracking technology has developed in its use in research, but also the applied setting.

Studies in sport have typically used object trajectories (Cervone, Bornn, & Goldsberry, 2016; Gyarmati & Anguera, 2015) or match events (Gyarmati et al., 2014; Stanojevic & Gyarmati, 2016) in isolation. Tracking technologies often involve post-processing and additional information can also be added manually. Additional information may include the recording of match events (Gudmundsson & Wolle, 2014). Object trajectories and match event logs, when used in combination, may provide more context to what is occurring than using either one independently. For example, a match event recording of a shot does not necessarily account for the context in which the shot was taken. For instance, how close was the nearest defender, were there multiple defenders and what was their velocity? These are questions which spatiotemporal data can help answer. Thus, match events paired with object trajectories may provide a more in-depth and applicable understanding of what is occurring in competition (Bruce, 2016; Gyarmati & Hefeeda, 2016). For example, player tracking data has been used to improve the examination of a single match event in basketball. Instead of recording a shot as a discrete event, player tracking data has helped to improve the understanding of other factors surrounding that shot, such as players speeds, position and movement of the ball in order to understand shot type and selection (Bruce, 2016). This enables the playing styles of teams to be defined based on their statistical movement and team profile, as opposed to a summary of traditional discrete measures (Bruce, 2016). This style of performance analysis could continue to be furthered through applying analytical techniques paired with the development of tracking technologies, and an interdisciplinary approach to data collection and analysis.

Increased access and the improved feasibility around optical tracking technologies may allow for practitioners in both the applied and research setting to analyse different aspects of the game, which is not possible with notational analysis techniques (Sicilia et al., 2019). The challenge with these technologies is for practitioners to extract information and meaning from the data (S. Morgan, Williams, & Barnes, 2013). The large quantity of raw positional data collected in professional sport requires sophisticated analysis to gain insight from the data and answer complex questions (Andrienko et al., 2017; Bialkowski et al., 2014b; Bruce, 2016; Wei, 2016). Techniques in data mining and statistical modelling can aid in finding meaning and providing useable information and insights to coaches (S. Morgan et al., 2013). Furthermore, a gap exists in applying spatiotemporal data to inform disciplines alongside performance analysis, such as skill acquisition. Thus, an interdisciplinary approach could enhance the application of spatiotemporal data in research and applied settings.

2.1.2.3 Playing Area Subdivision

Player tracking and match event data can be challenging to work with due to the complex and chaotic nature of sport. A method to ameliorate this is to discretise the data by dividing the playing area into regions (Gudmundsson & Horton, 2017). Subdividing playing areas into regions can aid in the feasibility of analysing large datasets. These regions often use an imaginary grid or a square in the Cartesian system (Santos-Fernandez, Mengersen, & Wu, 2019). The subdivision of data collates individual location points together within a discretised region. The frequency of events occurring in each region offers a spatial snapshot of what occurred in a particular region (Gudmundsson & Horton, 2017). The use of playing area subdivision can be done for specific events, an individual or team movements. Playing area subdivision reduces the number of data points and results in a discrete, spatial distribution of player and event locations within a match (Gudmundsson & Horton, 2017).

Playing area subdivisions can vary depending on the sport, the type of analysis taking place and the amount of data available. A common approach is to divide the playing area into equal sized rectangles and treated with the same weighting or importance across a field (Gudmundsson & Horton, 2017). However, ground locations are not all equal; region location and importance should therefore be taken into consideration. Considering location and importance may aid in providing context to analysis. The size of these regions is important, and overfitting can be avoided through selecting size based on the amount of data available. Overfitting describes a model, which is generated specifically to a training dataset, but where the results are not generalisable or validated on a new or unseen test dataset (S. Morgan et al., 2013; Robertson, Back, et al., 2016). The simplest solution is to divide the field equally, however the behaviour of players is not necessarily uniform across these subdivisions. For example, within basketball, the three-point line alters the way teams play and an athlete's likelihood to shoot the ball and accuracy differs on either side of the line (Goldsberry, 2012). Similarly, in soccer, a defender's likelihood to tackle within or outside the penalty box differs (Gudmundsson & Horton, 2017). Thus, sport specific subdivision should be used. In soccer, the playing area has been subdivided with consideration to the penalty box (Camerino, Chaverri, Anguera, & Jonsson, 2012). Similarly, in netball using court markings and the shooting semi-circle (Browne, 2016) and in basketball around the three-point line (Goldsberry, 2012). Playing area subdivisions have been used in several sports to gain insights into different aspects of performance. In soccer and netball, pitch/court subdivisions have been used to simplify the match event data and group similar passes, where sequences of passes were identified by the zone they began and finished in (Borrie et al., 2002; Browne, 2016). Subdivisions in rugby league have been used to estimate the chance of scoring from certain ground locations (Kempton et al., 2016). These subdivisions enable researchers to more easily group data to extract answers to the questions being analysed.

Subdivisions of playing areas are especially critical in AF given the large field size which varies from ground to ground. AF fields have previously been divided into the four regions: the defensive 50 m arc, the defensive midfield, the attacking midfield and the attacking 50 m arc (Alexander et al., 2019; Ireland et al., 2019). However, the size of the region should be determined based on the aims of the analysis and quantity of data. For instance, large region sizes have been used to understand ball movement and field equity in AF (Alexander et al., 2019). In comparison, smaller region sizes could be used to understand shots on goal and provide more specific insights. Therefore, the appropriate subdivision of playing area is critical when exploring different aspects in sport.

2.1.2.4 Shot Charts

Shot charts are visualisations of shot location, frequency and outcome. These can be created for a single match or a group of matches. Shot charts have the ability to add additional contextual information surrounding a shot (Chang et al., 2014; Reich, Hodges, Carlin, & Reich, 2006). Shot charts have developed from a need to better understand variability in shot success rates. They can demonstrate location preferences to help understand both team and individual strengths which may be used for athlete development and informing strategy. Shots on goal can be broken down by the combination of three variables: the number, context and accuracy. Shot charts may inform offensive and defensive strategy in the applied setting (Reich et al., 2006). As technology has advanced, research has begun to explore more variables that can be included to inform a shot chart (Pocock, Bezodis, Davids, & North, 2018) and also calculate likelihood of a score in the lead up to the shot (Cervone, D’Amour, et al., 2016; Kempton et al., 2016; O’Shaughnessy, 2006). This have been used in the applied setting to make comparisons between individuals and teams.

Shot charts have been used to compare athletes and teams across seasons and careers. Further to exploring shots solely through court location, differences in shooting patterns exist for teams playing at home and away (Parker, 2011). A study compared teams playing at home and away, and found that in most regions the shooting was poorer at home games compared to away games (Parker, 2011). However, these unexpected differences may be due to a number of unaccounted influences on offensive success, such as the quality of the opposition (Parker, 2011). This reinforces the need for the ability to be able to add contextual factors to shot charts to create an accurate representation of what is occurring and why. However, there is limited research on these contextual factors and their influence on shooting and shot charts.

Several methods have been applied to understand shooting trends. Whilst shooting effectiveness has been explored, inconsistent methodologies have been implemented (Gudmundsson & Horton, 2017). Within basketball, shooting efficiency has been calculated using non-negative matrix factorisation to represent spatially distinct shot-types (Miller, Bornn, Adams, & Goldsberry, 2014). A vector Boolean-valued predictor variable has also been used to calculated likelihood of shot outcome, with linear models fitted to shot frequency, location and efficiency (Reich et al., 2006). Effective shot quality has also been computed using a least-squares regression function (Chang et al., 2014). More so, empirical Bayesian scoring rate estimator have also been used and fitted using sub-divided regions to predict the likelihood of success of a shot (Shortridge, Goldsberry, & Adams, 2014). Yet, these various techniques are uni- or bi-variate in nature and do not necessarily account for multiple factors, and therefore the context which influences a shot. This may include the quality of the defensive player, the number of close defenders, the difference in score, time remaining and the mental state of shooter. Numerous factors need to be accounted for, as a plethora of factors are influencing a shot in the applied setting, not just one or two.

A multivariate approach assists in accounting for the interaction and influence of multiple variables (Grimm & Yarnold, 1995). In rugby union, a multivariate approach to on-field goal kicking performance has been evaluated through linear mixed models, to determine patterns influencing goal kicking (Nel, 2013; Pocock et al., 2018; Quarrie & Hopkins, 2015). Players were ranked based on fixed effects: kick distance, angle, side of field and random effects such as player, venues, importance of kick and time remaining (Pocock et al., 2018; Quarrie & Hopkins, 2015). This study showed similar effects between individuals, in that increased distance from goal led to a significant decrease in success, whilst venue had a small effect. However, how these and other variables interacted with one another in match conditions was not explored and thus reduces the ability to apply the findings in the applied setting (Quarrie & Hopkins, 2015). In a separate study, the interaction of altitude, shot angle and distance were combined to estimate the probability of a successful kick (Nel, 2013). The exploration of the interaction of variables needs to be continued in research, as in sport these variables are interacting and influencing the performance. Hence, it is important that multiple variables are analysed as such to provide an accurate analysis.

In basketball, shot charts have been used extensively to gain an understanding of the strengths and weakness of an offensive player by exploring the spatial components of the shot (Goldsberry, 2012; Reich et al., 2006). Location is critical in assessing the quality and likelihood of shot success in basketball (Reich et al., 2006). Shot outcome is dependent on several conditions, including the angle and distance to goal, defence and the shot taker (Galbraith & Lockwood, 2010; Pappalardo & Cintia, 2017). Within basketball, field goal percentage (FG%) is one of the main metrics used to evaluate a player's ability to score. However, a player who shoots the ball on the edge of the key, and another who shoots from outside the 3-point line, are both considered as field goal shots. Both are measured by the same statistic even though the execution of a 3-point shot is more difficult (Piette, Anand, & Zhang, 2010). Accordingly, shot charts have been used to study shot locations and outcomes in basketball, to remove the distance bias found in FG% and add insight from an offensive and defensive perspective (A. Franks, Miller, Bornn, & Goldsberry, 2015b; Goldsberry, 2012;

Reich et al., 2006). Using shot location data and providing context to shots, including playing position, number of shots per minutes player and success rate, a greater level of insight can be provided about the efficiency of individual players (Piette et al., 2010). An understanding of these spatial components could add value to not only coaches but also recruiting staff. Importantly, to make comparisons between players, a baseline is required. A *k*-means analysis has been used in basketball to identify five different clusters in which different playing positions would shoot. For example, a centre is more likely to shoot from under the ring compared to a shooting guard who will most likely be shooting from around the 3-point range (Piette et al., 2010). In this analysis, the angle from the ring was not included, however this can increase or decrease the difficulty of a shot, and therefore affect the outcome of the shot (Piette et al., 2010). Earlier studies have accounted for both distance and angle to show variation in shot frequency and accuracy occurs with changes in angle from the ring (Reich et al., 2006). Future studies should aim to include multiple variables such as shot type, angle, match context and defensive influence in the analysis.

Shot charts are not limited to basketball. Parallel research has been conducted with hitting zones in sports such as tennis, cricket and baseball (Hand & Watkins, 1986; Moore, Turner, & Johnstone, 2012; Pingali, Opalach, Jean, & Carlbom, 2001; Wei, Lucey, Morgan, & Sridharan, 2016). The purpose was to understand an individual or a team's strength and weaknesses around where they can hit the ball. In tennis, this processed has been advanced and used to forecast the next shot (Wei et al., 2016). Shot trends have also been considered in AF. Within AF, shots from varying distance and angles can have equal opportunity of scoring. For example, a shot close but on a tight angle could have the same chance of scoring as a shot from further away but on a less acute angle (Galbraith & Lockwood, 2010). This research did not seek to create a shot chart, instead, it aimed to understand which areas of the ground had approximately the same opportunity for scoring (Galbraith & Lockwood, 2010). While shot charts have been created in multiple sports, further development is possible.

Further methodological developments are required to progress the use of shot charts from a simple descriptive summary to account for context surrounding shots and increase their application. (A. Franks et al., 2015b; Reich et al., 2006). As data collection and analysis increases in sport, the ability to compare aspects of game play and game context has increased. Shot charts have been criticised as they typically do not account for inherent complexities, the connectedness between players, the environment and the game situation (A. Franks et al., 2015a, 2015b). These contextual factors may influence the decision-making process around the shot, and therefore explain some of the causal factors of shot outcome (Galbraith & Lockwood, 2010; Hobbs et al., 2018; Mackenzie & Cushion, 2013; McGarry, 2009). For example, shot charts used to determine a player's shooting ability may be assessed on a limited number of shots which can lead to sampling errors, overfitting and unstable results (Marty, 2018). Shot charts also do not necessarily account for the influence of defensive and addition or removal of pressure due to match context, (e.g., period of the game, scoreboard etc., see Pocock et al. (2018) for exception). Shot charts need to continue to develop to provide insights into shooting trends. Analysis should also attempt to account for the events preceding the shot.

Acknowledging the differences which may occur in the lead up to a shot is an area often overlooked with shot charts in the applied setting. For example, in basketball, a 'catch and shoot' shot is much more likely to score compared to shooting off the dribble (Chang et al., 2014). A 'catch and shoot' shot is also less affected by the closeness of a defender due to the reduced time in possession (Chang et al., 2014). Similarly, in AF an understanding of the shot type is critical, whether a shot is taken in general play or as a set shot will alter the likelihood of scoring even when taken from the same location. Further research is required to understand how these contextual differences surrounding shot type are required. An understanding of these contextual variables may aid in improving an understanding of how these influence an athlete's ability to take a shot on goal. This may aid coaches in training design as well as tactical decisions. Decision-making around shot selection can be built into models. A theoretical model has been proposed in basketball to explain the optimal shot (Changa, 2017). Yet, shot charts are still limited in practice, as a result of the need to continuously update data, communicate model outputs and the data required, such as the impact of defence, to gain insights into individual shooting trends.

Defensive Shot Charts

Conventional statistics across many invasion sports place more emphasis on offensive aspects of the game compared to defensive aspects (Goldsberry & Weiss, 2013). Historically, measures of defensive performance have been based on notational analysis of physical events, such as blocks, spoils and rebounds (Gudmundsson & Horton, 2017). Research has also attempted to account for more variables such as defensive intensity, player density and shot difficulty (Aharoni & Sarig, 2012; Bocskocsky, Ezekowitz, & Stein, 2014; Changa, 2017). This has been a major criticism of basketball research, where aspects of situational variables including shot difficulty, shot selection, team tactics and time between shots are not controlled or accounted for (Bar-Eli, Avugos, & Raab, 2006; Gilovich, Vallone, & Tversky, 1985; G. Smith, 2003). Therefore, adding the defensive involvement is important for shot chart research in future.

The defensive team influence an offensive team's shooting options. Defensive shot charts have been created and analysed to gain an understanding of where individual defenders were allowing shots to be taken from, as well as any changes in frequency and accuracy compared to the offensive player's norm (A. Franks et al., 2015b). Defensive effectiveness has been proposed to consist of additional variables such as spatial dominance, an ability to prevent a shot from occurring, an increase the number of unsuccessful shots compared to the norm or being able to stop a player receiving the ball (A. Franks et al., 2015b; Goldsberry & Weiss, 2013; Gudmundsson & Horton, 2017). Changes in specific defensive matchups have also been measured to understand how offensive output are influenced by defensive matchups and whether help is provided in defence (A. Franks et al., 2015b). This was achieved by using spatiotemporal data to determine matchups, and then recording all shots and their outcome by defender, as opposed to the shot taker (A. Franks et al., 2015b). The ability to characterise the defence is possible through the combination of player tracking, visualisation tools and statistical modelling (A. Franks et al., 2015b). However, due to the dynamic nature of invasion-style sports, it is very difficult to pinpoint a single defender to a shot being taken, as often defenders will assist each other by either leaving their player or switching players. As such, this static approach provides a snapshot of what is occurring at the defensive level, however it is not a complete, dynamic model.

In addition to shot chats, an understanding of defensive tactics, mindset and mode of play may provide more context to defensive intent, and therefore an understanding of the influence of the defence on offensive output. Through information about shot quality, a more accurate representation of a team’s defence could be achieved. Whilst limitations still exist in the exploration of defensive shot charts, they can provide contextual information and therefore a better understanding about what is occurring in competition. As a tool, shot charts will continue to improve alongside technology.

2.1.2.5 Modelling Expected Goals

Shot charts have progressed from describing what has happened to predicting a potential scoring opportunity from varied locations. The extension of shot charts has led to the generation of metrics such as Expected Goals (xG), Expected Goal Value (EGV), Expected Point Value (EPV) and Expected Points (xP) (Rathke, 2017; Spearman, 2018; Wei, Lucey, Morgan, & Sridharan, 2013). These metrics represent similar values, but the naming depends on the terminology used in the respective sport. Expect value models typically consider different variables which may influence the shot on goal outside of just the location of the shot.

These are constraints such as ball location, time in possession, opposition pressure and type of play (i.e., general play or set shot).

Through the use of various contextual and spatiotemporal features, the likelihood of a shot resulting in a goal can be calculated. This offers the probability of scoring at different stages throughout a chain of possession, by applying a probabilistic model to player and ball tracking data. Decision-making can be estimated on the influence of the spatial configuration of players and the likelihood of scoring (Fernández, Bornn, & Cervone, 2019; Hobbs et al., 2018). An attempt to understand the likelihood of a successful play has been explored in sports such as basketball (Cervone et al., 2014), soccer (Fernández et al., 2019; Spearman, 2018) and ice hockey (Schulte et al., 2017).

An expected value model can be used to compare a team's actual goals against their expected value to determine whether the team or individual performed above or below expectations and offers an indication of a team efficiency. If a team can score more than their expected value, it may indicate better skill execution to the norm. This is true if conversely their score is below the expected value, skill execution may be below the norm. This has also been used as a comparison to give an indication of match outcome in small case studies (Rathke, 2017). A major limitation of this comparison is that it does not account for the opposition defence. A solid defensive team would make converting opportunities harder than against a weaker defensive team from the same location. Whilst the defence is often not accounted for within the analysis, they are sometimes rated for their effectiveness by how many goals are scored against them versus the expected goals against. Within AF, expected value style models have been limited. The equity of pitch location has been calculated (O'Shaughnessy, 2006), however the combined use of spatiotemporal and match event data to understand performance and expected value has not occurred to the level as some other invasion sports.

2.1.3 Performance Analysis in Australian Rules Football

Australian Football is a complex sport with dynamic interactions, which makes the subjective and objective analysis of individual and team performance difficult (McIntosh et al., 2019). Within AF, performance has been measured across a range of components including physiological output (Sullivan et al., 2014b), match movements (Wisbey, Montgomery, Pyne, & Rattray, 2010), performance indicators (Robertson, Gupta, & McIntosh, 2016) and other factors such as opposition ranking and match location (Fahey-Gilmour, Dawson, Peeling, Heasman, & Rogalski, 2019; Lazarus, Hopkins, Stewart, & Aughey, 2017; Robertson & Joyce, 2018). Performance analysis in AF has developed since dynamic programming was first applied to AF in 1998, where the benefit of conceding a behind so as to gain possession was determined (Clarke & Norman, 1998). Match events continue to provide insight into performance trends in AF.

In contrast to other invasion-style sports, such as American Football or Rugby, where a 'phase of play' is clearly defined, AF is free flowing which creates additional dimensions to analysing game styles (O'Shaughnessy, 2006). In the early stages of consideration, lapsed-time video analysis was used to gain an understanding of the physical demands of AF, and to determine the differences in movement patterns between different playing positions (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004b). Tracking technology, such as GPS, have been used to examined distance travelled, velocity and acceleration of players in AF (Cummins, Orr, O'Connor, & West, 2013; Wisbey et al., 2010). This data can help to understand player output and physical loads (Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010; Cummins et al., 2013; Wisbey et al., 2010; Wisbey, Rattray, & Pyne, 2008). However, the insights which can be gained from GPS are limited, as they do not account for match context, skilled performance or how physical output influences skill. These factors contribute to the total physical load placed on a player, and ultimately affect performance and therefore should be considered to gain the most holistic picture.

Various data mining techniques have been used to explore which performance indicators can best explain match outcome in AF. Performance indicators refer to actions or events which occur in competition (Hughes & Bartlett, 2002). In AF, statistics have been used to assess individual influence upon the outcome of an entire game by using eleven commonly reported performance indicators such as, kick, handball, mark, goals, inside 50s and clearances (Robertson, Gupta, et al., 2016). Findings from this study demonstrated that team strategies which achieved a spread of goal kickers were more successful (Robertson, Gupta, et al., 2016). Continuous time Markov chain models have used event categories to explore time, distance and speed with match events in AF (Meyer, Forbes, & Clarke, 2006). Additional research has been conducted to determine the extent to which 13 performance indicators can be used to explain match outcomes through Partial Decision Tree (PART) (McIntosh, Kovalchik, & Robertson, 2018). The PART model found seven rules which could predict match outcome at 79.3% accuracy. However, in order to generate these rules, the assumption was made that the sum of a team's players combine to form the measurement of team performance. Additionally, using a logistic regression and decision trees, a study revealed that differences in kicks and goal conversion between competing teams was the most influential factors in explaining match outcome (Robertson, Back, et al., 2016). This study used publicly available data for two seasons of the Australian Football League. Exploring the total number of events in a game is shown to be able to predict overall match outcome (Robertson, Back, et al., 2016).

Scope exists to enhance these findings with improved data and analysis techniques. Clubs within the league have access to a greater number of performance indicators which could offer more insight into which indicators are best at predicting winning outcomes. Additionally, differences in teams playing styles should be included in the analysis. More data could make the analysis of individual teams possible and this could aid in understanding how different teams' value different actions (Spencer et al., 2016). Match outcome research has become more specific by breaking the game down into quarters to understand differences within a match

(Spencer et al., 2016). This allowed more specific insight into differences between quarters rather than confined to a whole game (Spencer et al., 2016). However, to break the play down into smaller segments and explore how an individual disposal influences a possession chain is yet to be investigated in AF using tracking and match event data. Understanding AF as a dynamic system may allow for increased understanding of the affordances and functional behaviours which occur (Pill, 2014).

Performance in AF has often been determined by the frequency of different match events and performance indicators. However, when indicators of performance are isolated or discretised, they do not provide the context required for the accurate representation of match play. For example, using GPS data to measure physical output, spending more time in high velocity bands (high speed running >14.4 $km.h^{-1}$) or travelling a greater distance may not equate to improved match outcomes (Sullivan et al., 2014b). Research in basketball and soccer has also explored how increased physical distance travelled does not necessarily equate to improved performance (Andrienko et al., 2017; Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2016; A. Franks et al., 2015b; Lucey, Bialkowski, Monfort, Carr, & Matthews, 2014). Physical output and skilled match performance have been analysed together in AF research to understand how these factors interact, and this may provide a better indication of performance (Corbett et al., 2018; Corbett, Sweeting, & Robertson, 2017, 2019). Future performance analysis research should continue to seek to understand how physical and skilled factors interact, and not treat datasets independently.

Performance analysis has been used to improve multiple facets of AF. Performance analysis can help decision-making processes which relate to individual and team performance (McIntosh et al., 2018), such as assessing the predictive value of the draft combine and how draft position does not reflect career outcomes (Gogos, Larkin, Haycraft, Collier, & Robertson, 2020). Furthermore, statistics can be applied and used to measure player involvement and how this is associated with team success (Stewart, Mitchell, & Stavros, 2007). Individual and team performance questions can be answered though the use of spatiotemporal and match event data. The use of spatiotemporal and match event data to understand coordinated movements at player and team level is limited in AF (Spencer, Morgan, Zeleznikow, & Robertson, 2017b). However, it has also been used to determine collective team behaviours (Alexander et al., 2018; Alexander et al., 2019). Equity maps, based on manually collected event locations from the 2004 and 2005 Australian Football League seasons, have been developed to estimate the net value of an action on the field (O'Shaughnessy, 2006). Despite this wide-ranging research, due to the complex nature of AF, there is an absence of objectively quantifying outcomes which are a result of player actions. A lack of access to spatiotemporal data has reduced the ability to conducted investigations in these areas (Spencer et al., 2016). Spatiotemporal data is not only important in understanding what occurs in competition, but also in training.

Future research is required to understand unknown aspects of the AF competition and training environments. Limited research has been conducted into the differences and similarities which exist between training and competition setting (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004a; Ireland et al., 2019; Pill, 2014). The majority of research conducted in this area has been surrounding physical outputs, with little research focus on the skill demands of the sport (Ireland et al., 2019; Ritchie, Hopkins, Buchheit, Cordy, & Bartlett, 2016). Recent work has begun to explore both physical and skill data simultaneously (Corbett et al., 2019). However, an early study proposed that AF training should be representative of competition, in line with the old coaching adage of "train as you play" (Dawson et al., 2004a; Pill, 2014). This has begun to be explored in AF through the use of constraints (Ireland et al., 2019). However, many constraints and their interaction are yet to be measured in training and competition settings.

Australian Football is a sport where players travel the field freely and perform both offensive and defensive roles. However, the offensive and defensive roles are not recorded and analysed equally. Conventional metrics are used to describe offensive aspects of the game, including possessions, disposal efficiency, goals, assists, clearances and score involvements. However, there are limited metrics for defence, where measures are often limited to pressure acts, spoils and tackles. The limited defensive measures demonstrate the imbalance between offensive and defensive metrics. This may be partially attributed to the difficulty in measuring defensive measures compared to those relating to offence, as offensive actions are salient events which are easier to observe (A. Franks et al., 2015b). This is the case for most invasion-style sports. Future research in AF needs to focus on both the offensive and defensive impact to provide a more objective understanding of competition, and therefore enhance training design.

AF is a continuous sport; thus, research needs to explore match events and player movements, and also the sequential nature of this and how a match event is impacted by the events preceding it. To account for factors such as ground location, defence and the environment, a theoretical framework could be applied.

2.1.4 Theoretical Frameworks in Performance Analysis

Performance analysis has been criticised for not applying a functional theoretical framework to create further competitive advantage. A theoretical framework enables consistency in a process to judge and improve performance and helps enable consistent and translatable research (Glazier, 2010; Travassos et al., 2013). Multiple theoretical frameworks have been proposed in sport research, such as complex systems (Hulme et al., 2018; McLean et al., 2019), dynamical systems (Balagué et al., 2017) and ecological dynamics (Couceiro et al., 2016; Davids, Araújo, Vilar, Renshaw, & Pinder, 2013). Traditionally skills have been analysed and developed in isolation and controlled environments, however individuals need to be able to apply their skills in game situations and environments. Thus, applying an ecological dynamics theoretical framework may help to adjust practitioner training designs and more accurately measure aspects, such as technical proficiency (Bock-Jonathan, Bressan, & Venter, 2007). A reason for the lack of theoretical frameworks has been suggested as a result of sports coaches often being volunteers and ex-athletes who have learnt their coaching philosophy or analysis pedagogy through their playing experience (Lyle, 2002; Renshaw et al., 2009).

Without a theoretical framework, performance analysis has been described as “descriptive rather than explanatory” (Glazier, 2010). For instance, notational analysis typically describes performance, without accounting for *how* or *why* an action occurred (Araújo & Davids, 2016; Farrow & Robertson, 2017; McGarry, 2009). The use of a theoretical framework may help to guide and direct performance evaluation by coaches and practitioners (Araújo & Davids, 2016). Thus, the application of an underlying theoretical framework could aid in improving the impact and implementation of performance analysis in the applied setting. Furthermore, theoretical frameworks have been suggested to help continue the development of athletes from the novice to the expert level in both technical and tactical aspects (Bock-Jonathan et al., 2007). A theoretical framework can therefore aid performance analysis in providing a more holistic account of what has occurred and why.

A theoretical framework may help to provide consistency to research and applied methods. Research across multiple tiers of sporting competition could become more consistent in process and procedures with the application of a theoretical framework. Regardless of which theoretical framework is applied, consistently applying the same underlying framework to analysis can help to maintain uniformity in workflow, language, analysis techniques and visualisations (Balagué et al., 2017; Glazier, 2017; Robertson, 2020; Rothwell et al., 2020). Uniformity between these aspects is not limited to performance analysis and could aid in breaking down the siloed approach to sport science which currently exists in the applied setting (Glazier, 2017; Rothwell et al., 2020). The adoption of a theoretical framework may aid in reducing the disconnect between performance analysis research and practice.

2.1.5 Challenges and Opportunities in Performance Analysis

Performance analysis has become an established sub-discipline of sport science, however there are opportunities to progress further. Performance analysis applies parametric methods and investigates aspects of sport in isolation (box scores, game statistics), dynamically (ball possessions), and lastly complex analyses. This approach is typically based on linear thinking, which is limited to typically depicting the aggregate of individuals within a system (Ribeiro et al., 2019). This occurs without considering or accounting for how various components interact with one another, and the consequence of this interaction on performance (McLean et al., 2019). This reductionist approach does not allow for a feasible analysis of a complex system (McLean et al., 2019; Vaughan, Mallett, Davids, Potrac, & López-Felip, 2019).

In a reductionist approach, competition is analysed in components, and the sum of its parts are assumed to be reflective of the whole (McLean, Salmon, Gorman, Dodd, & Solomon, 2018). However, small changes made to a system can lead to large non-linear changes due to the system reorganising itself (McGarry, Anderson, Wallace, Hughes, & Franks, 2002). Ideally, analysis should aim to explore the complexity of a system as a whole. Non-linear analysis techniques can be used to analyse these complex interactions and better capture the whole picture (Low et al., 2019). In the future, performance analysis will need to progress from reporting levels of frequency counts of various actions towards the interactions which occur across both space and time, thereby reflecting the complexity of team sports (Ribeiro et al., 2019). Analysis techniques such as network analysis may provide a more detailed assessment of match events and enables a shift away from reductionist analysis techniques as this methods seek to understand the nexus of the environment (McLean & Salmon, 2019). Thus, for performance analysis to have impact in the applied setting, analysis techniques need to account for this complex and non-linear nature of sport.

In performance analysis specialised models are frequently used to attempt to understand performance. Issues can exist with the generation of specialised models as a result of the inability to validate them as often no ground truth exists for them to be validated against (Andrienko et al., 2017). In team sports, offensive metrics can be judged based on a score or success of an action, however often in defence this is not always feasible. One method of validation is to use indirect assumptions surrounding the way the sport is played. For instance, the aim of applying pressure to the ball carrier is to re-gain possession or stop the ball travelling towards the goal. Thus, as the ball gets closer to goal it is expected that levels of pressure will increase. A comparison of similar events across different areas of the ground may show variation in pressure measures, thus may provide an indirect way to validate a new metric (Andrienko et al., 2017). These validation methods are not definitive and subject to practitioner bias, athletic performance and a number of other factors. The validation of metrics is still not common in performance analysis and needs to become standard practice (A. Franks, D'Amour, Cervone, & Bornn, 2016). Thus, the challenge for performance analysis research is to begin to analyse the complex system as a whole and may aid in providing enough data and context to accurately validate a metric.

Performance analysis often investigates available variables, rather than exploring and developing variables for a greater understanding of performance (Hoch, Tan, Leser, Baca, & Moser, 2017; Mackenzie & Cushion, 2013). As a result, studies within the field often fail to provide information which can be applied in industry (Hoch et al., 2017). The questions that are asked in these areas may be defined as 'basic' or 'applied' questions. Basic research often discounts theories of underlying mechanisms of a particular phenomenon and are typically binary in nature. For instance, "If I control all variables, does variable x influence variable y". In contrast, an applied question would reflect more real-world situations and be more representative of variable influence on performance. For example, "does variable x, have any worthwhile effect on variable y, given all other variables" (Atkinson & Nevill, 2001). It must be noted that no difference in experimental rigour exists between these two, it is merely a contrasting type of research question (Atkinson & Nevill, 2001). Thus, performance analysis needs to better understand the variables which can be used in specialised models to understand performance, rather than just using the variables which are readily available. One source of information often neglected which may help explain performance is the experiential knowledge of coaches and athletes (Brackley, Barris, Tor, & Farrow, 2020; Greenwood, Davids, & Renshaw, 2012; Woods, McKeown, Rothwell, et al., 2020).

The transfer of knowledge between sport science and coaches is often lacking (Couceiro et al., 2016). Papers dating back to the 1980s have referred to the issues of bridging the gap in sports science research to the applied setting (Burke, 1980). Communication of findings is critical for work to be applied and have value (Burke, 1980; Reade, Rodgers, & Hall, 2008). Whilst, practitioners in the applied setting find peer reviewed research insightful and helpful, accessibility and implementation issues still exist (Fullagar, Harper, et al., 2019; Fullagar, McCall, et al., 2019). The generation of a unified approach to performance analysis, and sport science in general, could aid the efficient use of data (Balagué et al., 2017; Glazier, 2010, 2017). Experiential knowledge can also be used to inform and guide research directions which may aid the applicability of research (Rothwell et al., 2020; Woods, McKeown, Rothwell, et al., 2020). For example, Brackley et al. (2020) used semi-structured interviews to understand the intent and purpose of drills in swimming from a coach's perspective. The next stage of this research is to scientifically analyse these drills to determine whether they are targeting the areas of technique as intended by coaches. This research is guided by experiential knowledge which may enrich the practical nature of the research.

The use of technology has increased in performance analysis; however, its application is not standardised. This has led to issues in tactical analysis as it has been found to be inadequately structured (Ávila-Moreno, Chirosa-Ríos, Ureña-Espá, Lozano-Jarque, & Ulloa-Díaz, 2018). This may lead to misinterpretations of results due to differences in terminology and the inconsistent classification of finding (Ávila-Moreno et al., 2018; Sarmento, Anguera, et al., 2014). Misinterpretations could lead to an increased divide between the theory of research and the applied use of findings (Ávila-Moreno et al., 2018; Mackenzie & Cushion, 2013). This divide creates a larger gap between performance analysts, coaches and practitioners and can reduce the likelihood of the uptake of information surrounding tactical analysis (Ávila-Moreno et al., 2018).

2.1.6 Conclusion

Performance analysis is a growing sub-discipline of sport science. The incorporation of new technology has led to a large growth in data availability and quality, especially due to the development of tracking technologies. Yet, sport is a complex system and traditional techniques, such as notational analysis, are unable to feasibly analyse all factors and their impact. This has led to uptake of technology and analytical techniques in sport science to manage large datasets to create more impactful information. Currently, the application of a theoretical framework is not standard practice in performance analysis. However, performance analysis remains an area which would gain increased competitive advantage from utilising a theoretical framework and taking an interdisciplinary approach to guide future research and encourage its use in the applied setting.

2.2 Skill Acquisition

Skill acquisition theory explores how individuals progress in developing new skills (DeKeyser, 2007). Skill acquisition is an overarching term which explores behavioural and neurological variables which influence the central nervous system and one’s ability to learn or adapt a motor skill (Magill & Anderson, 2007). It is an interdisciplinary science of intention, action and perception (Seifert & Davids, 2012). The best practice of skill learning in sport can be difficult to quantify, due to sports chaotic nature and the many moving parts, ranging from the individual, competition tier to weather conditions. For both team and individual development, understanding these dynamic features is important for improving on-field performance.

Traditional skill acquisition practices have focused on the cognitive processing of skill development. This suggests that individuals should learn the ‘correct’ technique before experiencing competition environments (Renshaw et al., 2009). However, individuals may be able to achieve the required task outcomes through different co-ordination patterns, meaning there is more than one ‘correct’ method. This can be demonstrated as experts often show increased variation within their movement patterns, compared to their lesser skilled counterparts (Renshaw et al., 2009). The techniques applied in traditional coaching practice often centres around explicit verbal instructions and augmented feedback (Renshaw et al., 2009). This explicit learning style has been suggested to lead to skill failure under stressful situations, as the individual is thought to need to ‘reinvest’ in both conscious and cognitive processing to aid in controlling their movement patterns (R. C. Jackson & Farrow, 2005; R. S. Masters & Maxwell, 2004; Renshaw et al., 2009). Additionally, it has been proposed that movement patterns are not controlled by the higher levels of the central nervous systems, but rather draw on the lower levels of control which aid in regulating movement behaviours sub-consciously (Renshaw et al., 2009). Thus, an important aspect of skill acquisition is accounting for the differences which exist between individuals and environments (Dunwoody, 2006).

Training design is an element of skill acquisition, where coaches should balance development of skill alongside the physiological requirements of athletes (Farrow, Pyne, & Gabbett, 2008). To understand the elements of training design the difference between open and closed drill types has been explored. Open or game-based drills involve skill and physical elements, whereas closed skill drills are more focused on repetition with decision-making factors removed (Farrow et al., 2008). Both drill types have different purposes, alongside pros and cons. For instance, anecdotal evidence exists which suggests that ‘lazy’ players may use open drills to ‘hide’ and thus reduce the amount of physical work required (Farrow et al., 2008). Yet, open skill drills still elicit higher movement demands and physiological loads (Farrow et al., 2008). Whilst closed skill drills may increase the number of disposals to improve technique, and this is coupled with minimal decision-making opportunities (Farrow et al., 2008). Furthermore, the potential benefits of a periodised approach to skill learning and training design have not yet been fully quantified (Farrow & Robertson, 2017; Otte et al., 2020; Otte, Millar, & Klatt, 2019). Periodisation is where systematic variations to training design are implemented across short- and long-term time periods with the aim of improving performance (Kiely, 2012). Moreover, when greater variability of difficulty levels are incorporated in training it is proposed to have led to improved performance in competition (Otte et al., 2019; Robertson et al., 2019; Travassos, Duarte, Vilar, Davids, & Araújo, 2012). Transferring skill acquisition research for coaches is a critical component for the uptake of research in the applied setting.

Coaches play a key role in replicating competition environments and creating productive learning environments in training to best promote skill acquisition (R. Masters, 2008; Mooney et al., 2016). Coaching science has been criticised for conducting research which has had little impact on coaching practice (Bishop, 2008). Alongside this, it has been demonstrated that coaches can sometimes lack empirical or evidence-based groundings to support their pedagogical approaches (Davids, Renshaw, Pinder, Barris, & Greenwood, 2016). This may be due to the lack of empirical understanding of constraints and their influence within the competition environment, alongside complicated and misused terminology (Araújo, Davids, & Passos, 2007). Coaches play a vital role in improving on-field performance, thus more research is required to utilise and be informed by coach experiential learning (Rothwell et al., 2020). Additionally, literature has often focused on the physical demands of sport (Bangsbo, 2014; Mohr, Krustrup, Andersson, Kirkendal, & Bangsbo, 2008; Quarrie, Hopkins, Anthony, & Gill, 2013; Wisbey et al., 2010; Wisbey et al., 2008). Moreover, research is should explore physical and skill requirements symbiotically (Corbett et al., 2018; Corbett et al., 2017, 2019). This information could help to inform coach decision-making about the design of training environments by accounting for the dependent relationship between skill execution and physical output to best promote skill acquisition. The application of a theoretical framework could help make research more applicable.

A major hurdle for practitioners in skill acquisition is differences in individual learning styles and speeds. Individuals adapt movement behaviours differently and these differ in distinctive circumstances (Araújo & Davids, 2011). The application of a theoretical framework could help in accounting for these differences. Theoretical frameworks have attempted to understand and explain the interplay and interaction of many complex dynamic systems. Theoretical frameworks, such as ecological dynamics, attempt to improve match performance through the increased understanding and ability to transfer learning from training to competition (Brackley et al., 2020; Maloney, Renshaw, Headrick, Martin, & Farrow, 2018). The understanding of performance in sport is derived from theoretical knowledge, which has grown from a number of theoretical frameworks (Greenwood et al., 2012). Consequently, most skill-based training programs implicitly or explicitly use a conceptual or theoretical framework as a basis (Handford, Davids, Bennett, & Button, 1997). Coaches, via experiential learning and knowledge, may intuitively apply these frameworks in a non-formalised manner (Greenwood et al., 2012). Ecological dynamic is a theoretical framework which attempts to account for this (Araújo et al., 2007). The application of a theoretical framework in skill acquisition should therefore account for the individual's adaption to complex, interconnected variables and events. The following sections will focus on ecological dynamics, representative learning design (RLD) and the constraints-led approach (CLA).

2.2.1 Ecological dynamics

The relationship between skill acquisition and understanding how and which constraints influence performance in competition is vital (Davids et al., 2013). Constraints are understood as the boundary in which functional movement solutions emerge (Davids et al., 2008), and are commonly classified into individual, task and environmental categories (K. M. Newell, 1986). Understanding the impact of constraints on skilled performance is therefore central to the design of activities intended to promote performance and learning in sport. Ecological dynamics has been proposed as a reliable framework which may explain the emergence of skill acquisition and performance through the interaction of the individual-environmental relationship (Travassos et al., 2012). This theoretical framework can provide an integrated approach to understand and explain human behaviour (Seifert, Papet, Strafford, Coughlan, & Davids, 2019).

Ecological dynamics is a contemporary theory of skill acquisition, which posits that behaviour is an emergent property of the functional behaviours which satisfy a unique set of interacting constraints (Araújo & Davids, 2011; Davids et al., 2013; Vaughan et al., 2019; Woods, Jarvis, & McKeown, 2019). The theoretical framework of ecological dynamics stems from ecological psychology and dynamical systems theory (Gibson, 1979; Kelso, 1995; K. M. Newell, 1986; Seifert et al., 2019; Uehara, Button, & Davids, 2019). Ecological dynamics is an alternative to the enrichment and systematic design theories of learning (Brunswik, 1956; Davids, Araújo, Hristovski, Passos, & Chow, 2012; Pinder et al., 2011).

Ecological dynamics has the ability to provide an encompassing hypothesis on human behaviour within sport (Seifert, Araújo, Komar, & Davids, 2017). An ecological dynamics approach suggests a non-linear interaction exists between system components (Seifert et al., 2019; Vaughan et al., 2019). The theory of ecological dynamics provides the relevant scale of analysis of the individual-environment relationship, as opposed to exploring the two separately (Davids et al., 2013). The individual-environment relationship forms the foundation for learning design (Araújo et al., 2006; Renshaw, Chow, Davids, & Hammond, 2010). This relationship is important as for individuals to perform successfully, they need to have the ability to adapt their actions in changing environments and exploit information made available (Araújo & Davids, 2018; Araújo, Davids, Chow, Passos, & Raab, 2009; Davids et al., 2012). The accounting for this relationship helps to explain human behaviour.

Ecological psychology and the ecological dynamics framework have helped give an understanding of human behaviour. Prior to ecological dynamics the main theoretical underpinning for understanding motor skills stemmed from cognitive science in an information processing approach. In cognitive science, decision-making is presumed to be created through a centralised controller; it is a mental model that organises and regulates this process (Araújo et al., 2009). However, a cognitive approach for movement has been refuted as it displaces the original problems of behavioural decision-making towards a pre-existing internal structure and emphasises the development of cognitive aptitude (Araújo et al., 2009; Davids & Araújo, 2010; Turvey, Shaw, Reed, & Mace, 1981). The suggestion was that as opposed to being localised internally, control of decision-making occurs in the individual-environment relationship as a result of the relationship between action and perception (Araújo et al., 2009; Correia, Carvalho, Araújo, Pereira, & Davids, 2019; Davids & Araújo, 2010; Davids et al., 2013; Gibson, 1979). This contrasting view to the cognitive framework proposed that behaviour is constrained by the interaction of the physics of the environment, the individuals own biomechanics, perceptual abilities and the specific task demands (Araújo et al., 2009; Warren, 2006). These aspects of ecological dynamics act across multiple levels. Ecological dynamics forms a holistic, wide-ranging theoretical framework which can be used for defining sports performance and human behaviour (Immonen, Brymer, Davids, Liukkonen, & Jaakkola, 2018).

Ecological dynamics has been proposed to act at three levels. The first being the movement coordination patterns and their dynamic relationship, this stems from a set of interacting environmental, individual and task constraints (Araújo & Davids, 2011; Seifert et al., 2019).

The second level is the need to reconsider the role of behavioural variability within skill acquisition and talent development (Seifert et al., 2019). Finally, the third level proposes that variability in coordination stems from a continuous co-regulation of perception-action coupling (Seifert et al., 2019). The understanding and application of these three levels may aid coaches in the development of training situations which resemble the randomness of competition settings. This allows for a coach to guide an individual to problem-solve in order to complete a task in a non-linear environmental and task constraints (Handford et al., 1997).

Within sport, ecological dynamics has attempted to provide a framework to identify and explain behaviour. Practitioners need to be able to accurately understand the interaction between the individual and environment to measure performance (Araújo et al., 2006; Browne, Morgan, et al., 2019; Vilar, Araújo, Davids, & Button, 2012). Ecological approaches to comprehending and improving motor performance have outlined the significance of examining both the physical and social environments where the activity occurs (Barris, Davids, & Farrow, 2013). The constant change in an environment is due to the complex spatiotemporal nature of sport. It has been demonstrated that interpersonal spatial and temporal interactions of attackers and defenders can influence the performance of the individual through the influence of opposition positioning, the ball and goal location (Vilar, Araújo, Davids, & Button, 2012). Research exploring the relationship between skill and fatigue has often examined decision-making and technical skill in separate study designs (Royal et al., 2006). However, the relationships between variables are often dependent on the individual. Ecological dynamics provides a framework to begin to account for and understand this interaction.

The ecological dynamics framework attempts to explain individual behaviour (Vilar, Araújo, Davids, & Button, 2012). Ecological dynamics posits that an organism's behaviour is related to and is informed by achieving a particular goal (Araújo et al., 2007; Brunswik, 1956). Expert performance has been described as the demonstration of solutions which evolve from self-organising system variables to account for and satisfy the unique set of constraints which interact with the individual in a given moment (Araújo & Davids, 2018). It proposes that an individual's performance requires an understanding and appreciation of the types of behaviours afforded by the environment (Araújo & Davids, 2018; Gibson, 1979). An affordance refers to the element of the environment which can be detected as information to support an action, and which is related to an individual's ability to apply it (Renshaw et al., 2009). The environment allows affordances which consists of properties which can afford different 'opportunities for action' for the individual (Gibson, 1979; Renshaw & Chow, 2018). This concept of affordances, from an ecological perspective, is predicated on the principle that the environment consists of information which regulates the movements of individuals (Davids et al., 2008; Renshaw & Chow, 2018). These concepts can be used to help understand behaviour in sport and physical education.

This framework is not isolated to elite athletic performance, but has also been applied in the physical education area. For instance, Teaching Games for Understanding (TGfU) advocates for a learner-centred environment, with an emphasis placed on exploratory learning within 'game-like' situations (Araújo et al., 2009). Students who underwent this style of learning performed better in tasks relating to tactical knowledge compared to those who were taught with a more traditional approach (Chow et al., 2007). Although similar to issues surrounding ecological dynamics, issues in study design and research methods have led to ambiguity within the data on the effectiveness of such a design (Chow et al., 2007).

Skill acquisition theory can be positioned within an ecological dynamics framework. Skilled athletes are able to alter their performance or actions as required, as they are not locked into a rigid solution but are able to be flexible or show 'dexterity' to achieve performance outcomes under a different set of constraints (Bernstein, 1966, 1996; Davids et al., 2012). The ability to be flexible in performance actions based on the current environment and task implies an ability to have an ongoing perceptual understanding and ability to alter an action to achieve the desired performance outcome (Davids et al., 2012). Accordingly, ecological dynamics has major implications for the design of training and the level of representativeness of task in training (Vilar, Araújo, Davids, & Button, 2012). The understanding of key informational constraints experienced by individuals in competition, and the replication of these in training, may allow for individuals to become better attuned to the environmental influence (Vilar, Araújo, Davids, & Button, 2012). This may allow for the training design to better reflect and provide opportunities which the individual faces in the performance environment (Travassos et al., 2012).

It has been proposed that practitioners and coaches should better understand how to represent the unstructured competition environment in the design of both training and research. This may help individuals to better comprehend and overcome competition-like situations and improve physical output (Barris et al., 2013). Whilst the competition environment is difficult to understand, more research is required within competition settings to accurately measure constraint interaction and offer a greater ability to create more representative training environments (McCosker, Renshaw, Greenwood, Davids, & Gosden, 2019; Pinder et al., 2011; Vaughan et al., 2019).

2.2.1.1 Degrees of Freedom

Degrees of Freedom can be considered to be the number of independent variables which can be controlled in a movement situation (Spittle, 2013). From a Gibsonian perspective, a system which contains many degrees of freedom can become a 'simpler' system should the appropriate constraint manipulation be established (Araújo et al., 2006; Shaw & Turvey, 1999; Turvey & Shaw, 1999). Additionally, degrees of freedom account for the number of ways the independent variables can be controlled within a system (Spittle, 2013). Typically, it refers to the number of independent variables of a system which can fit together in numerous ways (Davids et al., 2008). The proposition is that movement coordination emerges under interacting constraints, which harness the mechanical degrees of freedom of the movement system during the learning phase (Davids et al., 2008). A method to aid skill development is the simplification of movement control by locking joints or removing variables to reduce the degrees of freedom (Bernstein, 1966). These can then be gradually released during practice to allow the individual to learn to control and exploit the additional degrees of freedom. There are three sources of freedom within the ecological framework: i) external force fields of physical origin, ii) internal force fields of biological origin and; iii) information fields of psychological origin (Araújo et al., 2006; Shaw & Turvey, 1999; Turvey & Shaw, 1999). The concepts and application of controlling degrees of freedom may help to strengthen the transfer of skills from a practice task to the competition setting (Araújo et al., 2007).

2.2.2 Representative Learning Design

Ecological approaches to understanding performance have identified the importance of accounting for environmental influences (Araújo & Davids, 2011; Araújo et al., 2006; Barris et al., 2013; Brunswik, 1956; Davids et al., 2008). Traditional scientific principles are centred on controlled experiments, consequently, a large body of research has been conducted in controlled settings. Brunswickian psychology raises potential issues about the level of representativeness offered by many popular experimental models which have been designed to study movements influenced by dynamic environments (Brunswik, 1956; Davids, Button, Araújo, Renshaw, & Hristovski, 2006). Brunswik (1956) suggested that for research to achieve ecological validity it needs to be representative in design. A representative learning design (RLD) refers to the organisation of constraints within an experiment or training setting so that they include the context and circumstances from which the results are designed to mimic (Araújo & Davids, 2011; Brunswik, 1956; Pinder et al., 2011). Representative learning design was developed and founded upon the concepts of representative design and ecological psychology (Brunswik, 1956; Gibson, 1979; Headrick, Renshaw, Davids, Pinder, & Araújo, 2015; Pinder et al., 2011). An RLD approach to experimental design may aid the transfer of research to the applied setting.

For a study to be representative, individuals need to be able to interact with environmental constraints in training or the experimental setting that are similar to when performing in competition or the real-world environment (Brunswik, 1956; Davids et al., 2006). This feature of experimental design is termed ecological intercorrelation (Davids et al., 2006). For an experimental design to maintain a form of representativeness, it needs to keep key sources of perceptual information and actions together for the study to be able to determine influence upon actions (Davids et al., 2006). Representative design discourages the use of laboratory-based studies as a method of gaining an understanding of human movement systems due to the lack of representativeness (Brunswik, 1956; Davids et al., 2006). This concept can be applied in many fields, including sport, with the aim of better understanding human decision-making and performance.

The importance of RLD has been explored across numerous sports utilising multiple methodologies. Representative design is most prevalent in the study of adaptive movement behaviours within physical activity and sport (Davids, 2008; Pinder et al., 2011). Representative learning design has been proposed as a method to create training settings which may help individuals to self-regulate during their interactions within information-rich environments. The level to which an RLD is implemented has been explored in a number of sports. For instance, in AF, task constraint frequency and prevalence between training and competition settings has been explored (Ireland et al., 2019); in cricket, the difference between a how a batter reacts to a bowling machine and a human bowler was determined (Pinder, Renshaw, & Davids, 2009); in climbing differences between climbing on ice and indoor climbing were compared (Seifert et al., 2013); in basketball, the difference in outcome between taking a defended and undefended shot were explored (Gorman & Maloney, 2016). While these studies aimed to understand the similarities and differences between factors, the levels of functionality and action fidelity in these studies varied.

Functionality and action fidelity are two key principles of RLD. These aid in guiding the assessment of training tasks (Pinder et al., 2011). Functionality is the degree to which an individual can adjust their decisions and movements in the training or learning environment, with similar information sources present as per competition (Davids et al., 2013; Pinder et al., 2011). Action fidelity refers to the communication and transfer between movement behaviours in the competition environment and the training or simulated situation (Araújo et al., 2007; Pinder, Renshaw, Headrick, & Davids, 2013; Stoffregen, Bardy, Smart, & Pagulayan, 2003). Understanding and manipulating functionality and action fidelity within training design can allow for the dynamic and complex aspects of performance to be determined. This understanding alongside the combination of intention and maintaining the perceptual and action processes means fidelity should be viewed surrounding the performance goal intent, and not the “ideal” mode of performance (Pinder et al., 2013; Travassos, Araújo, & Davids, 2018). Action fidelity is high when movement responses are the same in the training and competition environment (Davids et al., 2013). Accordingly, low action fidelity may be the consequence of major differences in task or environmental constraints between the training and competition environments (Barris et al., 2013). Within sport, an understanding of the level of action fidelity would aid practitioners in evaluating the success of training design in representing competition settings (Pinder et al., 2011; Travassos et al., 2012). Research comparing the training environment to competition has been limited (Dawson et al., 2004a; Ireland et al., 2019; Krause, Farrow, Reid, Buszard, & Pinder, 2018). An accurate understanding of the competition environment is required to be able to design and implement changes with high levels of functionality and action fidelity in training design.

Research within the fields of sport pedagogy, physical education and coaching science have exhibited how the underlying principles of ecological dynamics framework may inform interventions and applied practice through a non-linear pedagogy (Chow et al., 2007; Pinder et al., 2011; Renshaw et al., 2010). Thus, an ecological approach to training encourages the design of continuous individual-environmental interactions. These interactions facilitate the emergence of functional decision-making and actions of athletes under competitive performance conditions in sport (Davids, 2008; Pinder et al., 2011). Understanding these interactions is crucial to allowing coaching practice and training design to reflect an alignment between the structure of training and the context of competition (Slade, 2015). A critical point for RLD is that experiments should aim to avoid removing phenomena from the training environment, so that only one variable remains, as this is removing the research from context (Araújo et al., 2007).

Traditionally in sport, the development of a technique has been centred around restricting movement and isolated drills, typically in a controlled environment (Farrow, Baker, & MacMahon, 2013; Slade, 2015). This was formed on the belief that to participate at competition level the skills required must first be mastered in training (Slade, 2015). However, even when technique and skill level was adequate in training, it often failed in competition (Slade, 2015; Turner & Martinek, 1995). Moreover, when compared with isolated training, activities such as small sided and conditioning games have been determined to be more relevant to skill acquisition and performance (Almeida, Ferreira, & Volossovitch, 2012). Therefore, whilst technique is important, rehearsing the technique in a competition-like environment may be more important to successfully complete a task in competition. The development of skills in a representative environments may also help improve tactical understanding of the action and decision-making process behind it (Slade, 2015). This is important as in competitive environments often little time is afforded and individuals are required to make decisions in an instant, and these are based on their interaction and interpretation of their aims, and their physical, emotional and cognitive states (Headrick et al., 2015). To perform successfully under variable conditions, it is essential to train in an environment which replicates competition (Crowther, Gorman, Spratford, Sayers, & Kountouris, 2019).

Research attempting to understand performance is not always representative of competition setting. Some studies when exploring concepts of learning and skill do not replicate the environment in which the skill needs to be executed. For example, in soccer, strategic decision-making in penalty kicks has been explored to understand how implicit and explicit learning may have different consequences (Navarro, van der Kamp, Schor, & Savelsbergh, 2018). It was found that both resulted in similar levels of decision-making, and the implicit training group achieve higher kicking accuracy (Navarro et al., 2018). However, the performance pressure, the strongest factor to influence penalty kicks was not explored (Jordet, Hartman, Visscher, & Lemmink, 2007). Thus, to understand the influence of learning styles on performance, experimental groups should be tested under competition-like environments wherever feasible.

Contemporary research suggests a shift toward experimental design which more closely resembles that of competition environments (Krause et al., 2018). In rugby union, the constraints surrounding a place kick were explored (Pocock et al., 2018). Place kicks occur outside the general dynamics of open play, but still occur under various constraints (Pocock et al., 2018). Variation in place kick success suggested that individual constraints such as emotion, physical output and mindset could alter and influence performance behaviours (Pocock et al., 2018). This study demonstrates that certain constraints influence kick success, and by understanding the influence of these constraints in competition settings, coaches can incorporate similar constraints into training (Pocock et al., 2018). Other studies have attempted to explore differences in high intensity training from a physiological perspective. For instance, in water polo, lap swimming was compared to a counterattack ball-drill (Botonis, Malliaros, Arsoniadis, Platanou, & Toubekis, 2019). This study found similar physiological stress placed on the body between the lap swimming and counterattack drill, however an increased anaerobic metabolism and higher rate of perceived exertion (RPE) for the counterattack drill (Botonis et al., 2019). Whilst this compared the physiological benefits, other aspects such as the potential tactical and technical benefit of completing a sport specific drill were not considered (Botonis et al., 2019). Representative experimental design has benefits, however improvements could be made and training settings which are relative to competition environments (Pinder et al., 2011).

The influence of constraints in training compared to competition is not fully understood in AF. However, some studies have aimed to understand the level of representativeness in AF. Studies have explored the frequency of constraint occurrence in training versus competition within AF (Ireland et al., 2019; Robertson, 2016). However, these have predominately focused on individual constraints and their prevalence, rather than their interaction. A multivariate approach could be used to better understand how constraints influence training compared to competition, and therefore the interaction of multiple constraints. Machine learning is a tool to make multivariate analysis more feasible (Robertson et al., 2019). The complexity of multivariate approaches and confusing terminology has limited the uptake of an ecological approach.

Research attempting to apply RLD has sometimes misinterpreted and misused terminology and concepts. For instance, ecological validity and representative design are different, but sometimes used interchangeably or incorrectly (Araújo et al., 2007; Pinder et al., 2011). Ecological validity, as it was originally conceptualised, refers to the validity of a cue (i.e., perceptual variable) in predicating a criterion state of the environment (Araújo et al., 2007; Brunswik, 1956). This can be measured through the statistical correlation between the cues available in both the experimental/training environment available to the individual and the distal standard variables of interest (Araújo et al., 2007; Brunswik, 1956; Pinder et al., 2011). In comparison, representative design refers to the degree conditions of an experiment reflect and represent the environment to which they are being generalised (Araújo et al., 2007). Thus, to help apply RLD, further education of researchers and practitioners is required, alongside a user-friendly platform for the implementation of the theoretical framework (Woods, McKeown, O'Sullivan, Robertson, & Davids, 2020).

An RLD aims to improve the applicability of research to accurately provide a sample of the environments in which participants perform (Greenwood et al., 2012). To increase the representative nature of a designed task, both perception and action need to be coupled, to provide adequate amounts of informational cues to the individual which are present within the competitive environment (Bonney et al., 2019; Pinder et al., 2011). For the research environment to be representative, it is important that researchers understand the level to which constraints affect the game and also how contextual factors do not only influence learning and outcomes individually, but also together, interacting with one another to alter the overall landscape of the environment and the decision-making process of the individual (Chow et al., 2007; Davids et al., 2012; Davids et al., 2008; Handford et al., 1997; K. M. Newell, 1986).

The manipulation of constraints can aid in creating drills with greater levels of specificity. Increased specificity of transfer can stem from existing intrinsic dynamics of an individual cooperating within the dynamics of a new task. When low specificity drill are designed general transfer may occur as the intrinsic and task dynamics do not align closely (Seifert et al., 2019). If the training stimulus is more general, the transfer will be more general (Seifert et al., 2019). Increased specificity can improve the perception-action coupling and lead to greater specificity of transfer (Seifert et al., 2019). For example, ice climbers gain some general benefit from training on indoor climbs, however they do not develop specific ice climbing skills such as crampon and ice pick use (Seifert et al., 2013; Seifert et al., 2016). The manipulation of constraints, both in the moment and over time, can aid in creating environments and habits which afford creative moments (Vaughan et al., 2019). This leads to a redesign of individual, environment and task constraints as learning occurs, so as to reflect and challenge the individual (Strafford, Van Der Steen, Davids, & Stone, 2018). The manipulation of constraints can aid to creating a training environment which is representative of the competition environment.

2.2.3 Constraints-led approach

Prominent ideas within RLD have been integrated into a Constraints-led approach (CLA) (Davids et al., 2006). Constraints are factors or demands placed on emergent properties of a system which can encourage or dissuade an individual from taking a certain action; they can both aid and inhibit certain behaviours (Correia et al., 2019). Within specific environments, variables, aims and intentions can alter how an individual behaves and, these behaviours can be adapted based on the relevant constraints (Davids et al., 2006; Headrick et al., 2015). The concept of constraints are present in many different scientific fields (e.g., maths, physics, biology and computer science) and often refers to the features designed to alter or direct the degrees of freedom within a system (Balagué, Pol, Torrents, Ric, & Hristovski, 2019). A CLA emphasises the role of perceptual-motor exploration throughout the learning phase in order to promote the acquisition of adaptable movement patterns (Komar, Potdevin, Chollet, & Seifert, 2018). Skill acquisition and performance outcomes are a result of the structure and dynamics of the environment, biomechanics, emotional and psychological factors and task constraints (Davids et al., 2013). A CLA has been adapted and utilised in sport.

A CLA may offer a different perspective in the way sport is observed, and therefore how constraints are manipulated in training (K. M. Newell, 1986; Renshaw et al., 2010). It has been suggested that the learning or acquisition of a new skill may result from managing interacting constraints (Davids et al., 2008). Constraints act on the individual learner, therefore the modification of constraints can alter the emerging skill acquisition and learnings, such as improving different coordination patterns (Komar et al., 2018). The manipulation of constraints can benefit individuals by promoting the trialling of different solutions and actions which may aid in improving the decision-making processes (Travassos et al., 2018). Accordingly, training tasks should incorporate the general aspects that underpin the functionality of individual skills surrounding anticipation and visual search patterns under a differing sets of performance constraints (Strafford et al., 2018).

Constraints shape the coordination of behaviour and can be broken into three categories. Firstly, individual constraints which can be structural (e.g., body dimensions, technical attributes), historical (e.g., development of resilience, experience) and functional (e.g., motivation, cognition) (Davids et al., 2013; Davids et al., 2008; Immonen et al., 2018). Secondly, task constraints, which in traditional sports are typically formed by rules (e.g., laws of the game, boundaries), task goals (e.g., passing, opposition influence) and instructional features (e.g., coach instruction, umpire feedback) (Cordovil et al., 2009; Greenwood, Davids, & Renshaw, 2016; Immonen et al., 2018; Orth, Davids, Araújo, Renshaw, & Passos, 2014). The final category is environmental constraints which can be physical (e.g., weather, light, gravity) or sociocultural (e.g., values, cultural beliefs, peer support) (Davids et al., 2013; Davids et al., 2008; Mooney et al., 2016). By understanding and manipulating these categories of constraints, coaches and educators can better design effective learning environments (Renshaw et al., 2010).

Constraints have a significant influence on performance outcomes. Small changes to constraints, such as game structure, rules or the environment, can cause dramatic changes to outcomes (Renshaw et al., 2010). Alterations to task and environmental constraints can allow for individual development in performance, refine movement patterns and alter the physiological and skill output of individuals (Fitzpatrick, Davids, & Stone, 2018; Gonçalves et al., 2017; Klusemann, Pyne, Foster, & Drinkwater, 2012; Travassos et al., 2018). However, not all constraints can be manipulated, such as an individual's history, but these still influence skilled performance. Similarly, sociocultural influences are predicated to influence eventual skill level and has been suggested as a reason for certain areas or countries producing the world’s best athletes in specific sports (Uehara et al., 2018). More research is required to understand the influence of constraints on performance.

Situational context has an impact on constraints, their interaction and influence. Research often does not take into account the interactive effect of complex conditions such as individual players and match context (i.e., game period) (Ruano, Serna, Lupo, & Sampaio, 2016). In the applied setting, the frequency of constraints has been collected in AF training and competition environments (Ireland et al., 2019). However, each constraint is considered in an isolated manner. A rule-based approach has been used to understand how constraints interact to influence performance in AF (Robertson et al., 2019). Future applied research should seek to understand situational context and the impact and interaction of environmental and task constraints. For instance, attempting to understand how the time remaining on a shot clock and shot distance influences performance in basketball (Sandholtz & Bornn, 2018), or quantifying the influence of task constraints on kicking in AF (Robertson et al., 2019). An improved understanding of constraints such as these could aid coaches in designing more representative training drills.

Coaches and educators may utilise a CLA to help design activities. A CLA functions on the assumption that dynamical systems are able to exploit the surrounding constraints in order to create a sustainable pattern within specific circumstances (Chow et al., 2007). A CLA has a clear emphasis on the learning processes through discovery (Davids, Araújo, Shuttleworth, & Button, 2003). Elite athletes are able to shape and affect these complex movement patterns within their environment (Buekers et al., 2017). This may demonstrate the emergence of functional and adaptive relationships between the individual and the environment (Renshaw & Chow, 2018). The concept of skill learning stems from the process of adapting and altering behaviours to suit the environment and understanding how they interact (Renshaw & Chow, 2018). Coaches and educators should account for this dynamic nature and individual differences to aid the design of training activities.

There are many different types of drills used in team sport training. Small sided games (SSG) are often used in the applied setting. These are prime examples of practice games designed using the underpinning philosophy of a CLA. A SSG can manipulate task constraints, such as space, number of players and rules (Canton et al., 2019; Coito, Davids, Folgado, Bento, & Travassos, 2019). SSGs have been shown to cause changes in individual and collective behaviour (Canton et al., 2019; Klusemann et al., 2012; Ometto et al., 2018). For instance, the change in playing numbers may allow teams to explore different configurations of space in short timeframes (Canton et al., 2019). A systematic review found that the manipulation of constraints created within SSGs altered different aspects of game play in training (Coito et al., 2019). Firstly, a team with fewer players or without a goal keeper had greater physiological responses and felt an increase in pressure compared to their counterpart team (Köklü, Sert, Alemdaroglu, & Arslan, 2015; Mallo & Navarro, 2008). Secondly, a team with fewer players demonstrates increased variability in the occupation of space (Coutinho et al., 2019). Thirdly, the effective playing area, shape and playing numbers affected attempts on goal (Coito et al., 2019; Vilar et al., 2014). The manipulation of constraints in SSGs can change behaviour, however the influence of these manipulations is not always constant or consistent.

The manipulation of constraints does not always produce the same outcome. Individual, environmental and task constraints interact with one another to influence behaviour. Constraints are dynamic, and their influence changes. The contextual features which shape an individual's cognitions, actions and decision-making process interact to alter behaviour and coordination (Figure 2.1) (Immonen et al., 2018; K. M. Newell, 1986). Constraints also interact with many seemingly unrelated components cooperating to different degrees and for varying lengths of time. These interactions are manipulated within research and training design to determine how an individual interacts with the current environment (Araújo et al., 2006; Balagué, Torrents, Hristovski, Davids, & Araújo, 2013; Correia et al., 2012). For instance, the behaviour of an individual may affect the circumstances following the chosen action, beyond the immediate result of the context in which the event took place (Araújo et al., 2009). There are multiple information sources available in the sporting environment, however the closer to the end aim, the way information sources are detected and regulated becomes more specific (Araújo et al., 2009). Therefore, measuring the influence of certain contextual factors is difficult. When the manipulation of constraints surpasses an individual's ability to cope with those constraints, this is referred to as a rate limiter. Rate limiters inhibit an individual from demonstrating the skills they have learnt, and therefore affects performance outcomes. Manipulation must therefore be used appropriately depending on the individual's skill level (Correia et al., 2019; Davids et al., 2008). The sporting environment requires athletes to have rapid cognitive processing (Almonroeder, Tighe, Miller, & Lanning, 2018). Within elite sport, the neuroanatomical formation and design of muscles, joints and their interaction form an important constraint upon the individual. Differences in all of these traits may lead to different outcomes whilst completing a task.

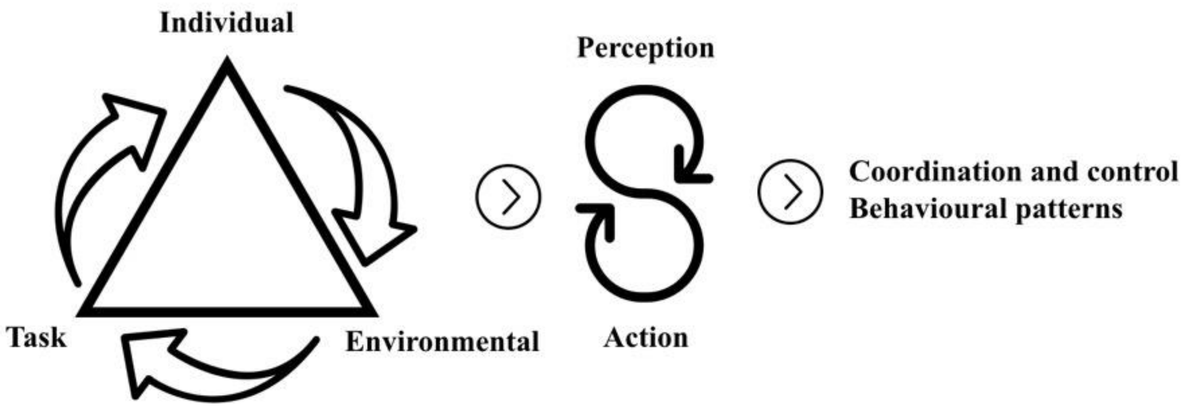

Figure 2.1 **Newell's model of constraints (K. M. Newell, 1986); individual, environmental and task constraints impact perception and action to influence behaviour.**

Constraints can change their influence within a system over time (Balagué et al., 2019). They are non-linear as well as non-proportional in regards to their influence on an individual's performance (Balagué et al., 2019). To understand the individual, it is important to account for their specific environment and therefore give context to the individual (Renshaw et al., 2009). For a training or experimental design to be representative, it likely depends on the coach or practitioner having an understanding of how the individual, environmental and task constraints are interacting to influence performance (Davids, Chow, & Shuttleworth, 2005; Renshaw et al., 2009). It is by identifying and then manipulating constraints that practitioners may design training environments that afford more opportunities for individuals to explore performance solutions and enhance creativity (Vaughan et al., 2019).

2.2.3.1 Individual Constraints

Individual constraints refer to the structural, historical and functional movements of individuals (Renshaw et al., 2010). Within the literature an individual may be referred to as an athlete, player, organism or performer somewhat interchangeably. Some criticism exists for the term ‘organism’ as this is usually used to describe biological functions, and does not imply that it includes cognitive processes (Hackfort, 2017). Thus, within this chapter, this constraint type will be referred to as ‘individual’. Individual constraints are categorised in three areas: structural, historical and functional (Davids et al., 2013; Davids et al., 2008; Immonen et al., 2018). Structural dimensions can be further sub-divided into those which remain relatively constant (height, weight etc.,) and those which change more quickly (motivation, fatigue etc.,) (Balagué et al., 2019). Each individual will approach learning and sporting situations in their own unique manner. Consequently, the assessment and measurement of the influence of individual constraints is difficult, but important.

Individual constraints can be difficult to measure due to their dynamic nature. An individual’s learning dynamics may vary even when task and environmental constraints are held constant (Davids et al., 2012). This can be a result of factors such as fitness, skill level and mental aspects (e.g., resilience and anxiety) changing and influencing skilled performance (Renshaw et al., 2010). Variables like motivation have been shown to influence physical output, and also to differ for individuals and change over the length of the season (Chong et al., 2018). These cognitive constraints mean that understanding how an individual interprets and influences their environment is critical. The manner in which an individual acts and their scope to improve is dynamic and evolving with the influence of task, individual and environment constraints (Araújo & Davids, 2018; Davids, Araújo, Seifert, & Orth, 2015). Furthermore, an individual's ability to cope with certain constraints changes with age. In baseball, skill level was compared across expertise and age (French, Spurgeon, & Nevett, 1995). Younger players were limited in which tactics they were able to apply due to their inability to complete the necessary skills (French et al., 1995). Thus, the example of experience demonstrates how individual constraints can impact skill execution.

The effect of cognitive processing is not limited to skill execution, but can also have a potential impact on injuries (Almonroeder et al., 2018). Individuals with slower baseline reaction times often display movement mechanics which may result in increased ACL loading during unplanned landing or cutting manoeuvres (Almonroeder et al., 2018; McLean, Borotikar, & Lucey, 2010). The risk can be further increased due to the influence of physical output and mental fatigue and its effect on cognitive processing (Almonroeder et al., 2018; McLean et al., 2010). A large body of evidence exists which suggests that fatigue produced through intense exercise may result in decreased cognitive processing ability (Almonroeder et al., 2018; Covassin, Weiss, Powell, & Womack, 2007; Konishi et al., 2017). Furthermore, the negative effects of fatigue on physical and skilled output stems from an individual's perception of effort and motivation, as opposed to actually reaching their physiological limits (Barte, Nieuwenhuys, Geurts, & Kompier, 2018). Future research should seek to further understand how individual constraints change over time and influence performance.

Individual constraints are important, however, they must be considered symbiotically with task and environmental constraints as they interact with one another (Araújo et al., 2009). Individuals are discrete entities, and actions may be a result of being embedded within a constantly changing environment and personal history. This makes it difficult to explain and apply the techniques that have been successfully implemented within other dynamical systems (Araújo et al., 2006). The importance of exploring an individual's history as well as the unique requirements of the task and environment are often overlooked within the discipline of coaching (Pinder & Renshaw, 2019). For example, place kick success in rugby has been explored by looking at match context and location, and suggested that research could be enhanced by including individual constraints such as emotion, physical output and thoughts, all which potentially interacted with perceptions to affect performance behaviours and outcomes (Pocock et al., 2018). Additionally, an individual's response to the same task and environmental constraints will vary based on their individual circumstance. To give meaning and context to the analysis of individual constraints, environmental and task constraints must be considered.

2.2.3.2 Environmental Constraints

Environmental constraints are described as those that are external to the individual, and cannot be deliberately altered in competition (Araújo et al., 2009; K. M. Newell, 1986). Environmental constraints can be categorised into physical and sociocultural constraints (Haywood & Getchell, 2009; Renshaw & Chow, 2018; Uehara et al., 2019). Physical constraints include light, weather, gravity and temperature (Chow et al., 2007). Socio-cultural constraints consist of factors such as crowds, upbringing and team expectations (Chow et al., 2007). These physical and sociocultural constraints influence performance (Chow et al., 2007). It has been proposed that sociocultural constraints heavily influence the impact of task and individual constraints (Araújo & Davids, 2011; Vaughan et al., 2019), due to social constraints being experienced differently by individuals (Chow et al., 2007). It has been proposed that young or inexperienced individuals are also often more strongly influenced by environmental constraints (Chow et al., 2007). This further demonstrates the dynamic link between the environment and the individual. The environment is an important aspect, however, can be difficult to control within training settings due it its intangible nature.

Within sport, individuals and teams display unique traits in playing patterns, and teams attempt to keep these consistent regardless of the opposition (McGarry et al., 2002). The environment is also a result of teammate and opponent location, therefore an athlete may influence their movement patterns based on the relative positioning of others (Duarte, Araújo, Correia, & Davids, 2012). This is due to the intertwined relationship between the perception, action and the intentions of the athletes acting within a complex system (Duarte et al., 2012). Given this complexity, acknowledging different environmental constraints is required. Knowledge of environmental constraints should be used to account for aspects such as the opposition and how movement patterns can be used to maximise the advantage of environmental constraints for a team and to minimise the impact of the opposition, alongside aspects such as the weather. Whilst environmental constraints are difficult to manipulate in competition settings, they can be more easily manipulated in training settings.

Environmental constraints should be acknowledged within analysis. The removal of these key sources of information can alter perception and the resulting action. This has been found to have a significant effect on an individual's timing and control of movement actions (Pinder et al., 2011). Environmental constraints need to be accounted for within the training environment. These constraints can be designed to allow for exploratory practice in varied training environments, and develop the capacity of individuals to independently discover numerous performance solutions and encourage flexible behaviour (Woods, McKeown, Rothwell, et al., 2020). This is important for the development of individuals who are able to adapt, self-regulate and be creative under various circumstances (Canton et al., 2019). The inclusion of critical aspects of the competition environment within training settings is important to help develop familiarity with the environmental properties, and therefore apply these skills within the competition environment as needed.

Environmental properties give rise to ‘specification’ (Araújo et al., 2006; Gibson, 1979). Specification is the perception of the environmental properties which are a result of the combination of the five senses: light for seeing, sound for hearing, chemicals and water for smelling and tasting as well as mechanical forces for touch. Within ecological design, these senses are combined to form a specific environment which influences the actions of an individual (Araújo et al., 2006). The information from an environment is available to an individual as an external resource which can be exploited (Araújo et al., 2006).

Environmental Constraint Example – Home Ground Advantage

A commonly studied environmental constraint is the concept of ‘home ground advantage’. This phenomenon has been the basis of considerable study since the 1970s (Clarke, 2005; Courneya & Carron, 1992; Fullagar, Delaney, Duffield, & Murray, 2018; José Gama et al., 2016; Lazarus et al., 2017; Nevill, Newell, & Gale, 1996; Pollard & Pollard, 2005; Schwartz & Barsky, 1977; Wolfson, Wakelin, & Lewis, 2005). Typically, three explanations are offered for the origin of home ground advantage: i) learning factors due to ground familiarity, ii) travel factors resulting in fatigue; and iii) disruption to routine and crowd factors and possible referee bias in some sports (Clarke, 2005). Thus, home ground advantage is more complex than simply the influence of environmental constraints. Home ground advantage has been found to exist in many invasion sports including AF, European soccer, hockey and basketball (José Gama et al., 2016; Gómez, Gómez-Lopez, Lago, & Sampaio, 2012; Lago-Peñas & Lago-Ballesteros, 2011; Lazarus et al., 2017; Schwartz & Barsky, 1977).

The findings of these studies have often consisted of statistical analysis to determine specific performance outcomes (i.e., winning and losing), without a theoretical rationale to help explain why these differences exist and to implement changes to mitigate negative effects (José Gama et al., 2016). Studies have shown that several factors influence the impact of home ground advantage, including the familiarity with facilities, total travelling distance and time, the importance of the game and if the opposition were 'rivals' (Clarke, 2005; Courneya & Carron, 1992; José Gama et al., 2016; Neave & Wolfson, 2003; Nevill et al., 1996; Pollard & Pollard, 2005; Wolfson et al., 2005). However, many of these studies explored just one aspect of the environmental differences and how that may affect performance, when these factors are actually interdependent. A recent study attempted to explore the relation between playing away by analysing travel-direction (east – west), the number of time zones crossed and distance, crowd size and team rankings (Fullagar et al., 2018). Within NCAA Division 1 football, playing at home on average was found to be worth an additional five points (Fullagar et al., 2018). Further research into the home ground advantage could look at individual teams and how the environment constraints differ from their home ground to when they play away. For instance, a large team may often play in front of 80,000 people, whereas when they play away the crowd size may be 40,000 and therefore the level of noise may not have as much influence on their performance. Additionally, within Rugby Union it has been suggested that it is not necessarily the size of the crowd, but the crowd proximity to the individual at a given time (Pocock, Bezodis, Wadey, & North, 2020). Furthermore, many environmental factors have flow on effects and influence more than one area of the game. For instance, crowd noise may influence umpiring decision-making, with the home team receiving more favourable decisions (Fullagar et al., 2018; Paradis, Carron, & Martin, 2014). These factors have been shown to influence game-related statistics with the home team having significantly higher means for goals scored, number of shots and attacking plays, in comparison the away teams have higher loss of possession and more yellow cards (Lago-Peñas & Lago-Ballesteros, 2011).

2.2.3.3 Task Constraints

Task constraints are formed by rules limiting or encouraging movement and behaviour. Task constraints include the spatiotemporal patterns available during an activity and are usually more specific to the performance context compared with environmental constraints (Davids et al., 2008; Handford et al., 1997). Task constraints are often pre-defined and set within competition, but can be altered in the training setting and are therefore considered the easiest constraint type to manipulate during training (Chow et al., 2007; Tan, Chow, Duarte, & Davids, 2017). These constraints are normally manipulated through the use of different size equipment, changing the rules of the game, altering playing numbers and size of the playing area (Farrow & Reid, 2010; Renshaw et al., 2010). Task constraints are understood to have a direct impact on the development of intentional behaviours and can also be manipulated through instructional constraints (Chow & Atencio, 2014; Davids et al., 2008; Renshaw et al., 2010). Small changes surrounding task constraints may lead to considerable changes in performance output (Pinder et al., 2011). Accordingly, task constraints may be the most important constraints to have a potential impact on learning (Chow et al., 2007).

The manipulation of task constraints has been proposed to impact a wide variety of aspects in sporting performance. The manipulation of task constraints, such as available space and equipment is considered an effective method for augmenting performance and improving movement patterns (Fitzpatrick et al., 2018; Kelly & Drust, 2009; Nimmins, Strafford, & Stone, 2019). Modification of these aspects can enable inexperienced individuals to complete aspects of skills and competition movements without the need to contend with all the constraints experienced in competition (Fitzpatrick et al., 2018). This may help aid athlete development by simplifying the degrees of freedom with which an individual needs to contend. Alterations to task constraints can also influence the technique an individual uses to complete the same skill. For instance, in AF goal kicking technique has been shown to change with increased kick distance (Blair, Roberston, Duthie, & Ball, 2018). Understanding that technique changes as the task changes is important knowledge for designing training and evaluating performance. In tennis, the use of altered racquet size for developing players is considered an effective method to refine movement patterns (Buszard et al., 2020; Fitzpatrick et al., 2018). The scaling of equipment has occurred as it is proposed to enable learning in young individual to have behaviours which more closely align with the full versions of the game (Fitzpatrick et al., 2018; Timmerman et al., 2015). The manipulation of task constraints can influence many aspects of performance.

Task constraints can influence tactical and physical aspects of sports performance. The manipulation of rules is a simple mechanism to influence in game actions (Almeida et al., 2012). As a consequence of rule changes, different attacking strategies have been implemented in squash (Murray et al., 2016). In various sports, the altering of task constraints in SSGs affects performance outcomes. For example, increasing the number of players on the field led to a decrease in the number of technical actions required per athlete and increase in physiological demands (Dellal, Hill-Haas, Lago-Penas, & Chamari, 2011; Klusemann et al., 2012). Yet, field dimension had less influence on the overall technical demands in soccer SSGs (Dellal et al., 2011). In field hockey, the manipulation of constraints within drills was determined to influence decision-making, technical skill and physical output (Timmerman, Savelsbergh, & Farrow, 2019). Behaviour varied depending on the constraints present, and thus the development of skills could be enhanced, from a technical, tactical and physiological perspective (Timmerman et al., 2019). This demonstrated the complex and varied interactions which exist and which influence decision-making (Araújo et al., 2006; Warren & Fajen, 2004). Furthermore, the manipulation of constraints may alter route switching behaviour. This may be a result of the desire to decrease the angle and distance to the target or goal and the repulsion or to maintain distance from the defender (Araújo et al., 2006; Warren & Fajen, 2004). This complexity is not limited to the task constraints, but also links with the environment.

Applied research which explores task constraints often makes assumptions about the environment. For instance, an AF study explored set shots and shots of equal opportunity based on distance and angle (Galbraith & Lockwood, 2010). This study assumed that the field conditions were dry and with no wind (Galbraith & Lockwood, 2010). Whilst this offers an opportunity to measure the effect of task constraints, it makes assumptions about the environment and thus may reduce the transferability and representativeness of the result. Future research should attempt to avoid making assumptions and incorporate factors such as the weather into the analysis.

Some applied research has attempted to measure the interaction between individual, environment and task constraints. This interaction is an important consideration in understanding performance. Altering task constraints by changing the number of players in small sided basketball games appears to be the largest influencer of the physiological demands and high intensity movement patterns of the individual (Klusemann et al., 2012). Similarly, in Rugby Union subtle changes to task constraints and individual factors have been shown to influence place kick execution (Pocock et al., 2018). Thus, the result of manipulating task constraints is also dependent on the environmental and individual constraints present.

2.2.3.4 An example of constraint interaction - Pressure

Pressure is a difficult concept to define, and is further complicated as individuals respond to it differently (Otten, 2009). One definition of pressure is “any factor or combination of factors that increases the importance of performing well” (Baumeister, 1984). Pressure can be measured and applied in many different ways, both physically and psychologically. In sport it can be broken down into dependent and independent variables. Dependent variables are based on the relative position of a defender to the ball or an attacking player and the goal (Andrienko et al., 2017). Independent variables include time remaining, period and scoreboard pressure

(Andrienko et al., 2017). The ability to cope with pressure, stress and anxiety is believed to be determined by an athlete's mental toughness, and is something which cannot yet be objectively measured (G. Jones, 2002; Russell, Jenkins, Rynne, Halson, & Kelly, 2019). Whilst pressure can be broken down into independent and dependent variables, it must be noted that it is ultimately the combination of multiple variables which result in an individual coping or succumbing to pressure under given circumstances.

Notational analysis has been used to record pressure. In Rugby 7s, an understanding of levels of defensive pressure has been used to determine how it affects pass types, evasive moves and ability to break lines (Griffin, McLellan, Presland, Woods, & Keogh, 2017). Defensive pressure was broken down into three categories: no defence, uncontested defence and contested defence. This study found that defensive pressure influenced pass type, evasive moves and line breaks (Griffin et al., 2017). Within AF human observation has been used to measure pressure and these have been described as ‘pressure acts’. Different types of ‘pressure acts’ are awarded varying values of ‘pressure points’ in AF. This method functions on a system where points are awarded for corralling (1.20 points), chasing (1.50 points), closing (2.75 points) and physical pressure (3.75 points) (Australian Football League, 2016c). Each type of pressure is accredited to the player applying it and is determined though human observation. These measures of pressure are subject to human interpretation and have subtle differences, but are both limited as they only observe the ball carrier. Pressure is created by the aspects of the whole environment and includes other factors such as passing opportunities and ground location. The use of spatiotemporal data may help alleviate some of the biases and limitations of human observation which are associated with notational analysis.

Spatial pressure is the level of available space for the attacking team. The more available space, the less pressure, and inversely the less available space, the greater the pressure. Andrienko et al. (2017) took this approach and explored pressure as the space around the ball carrier in soccer. Based on the level of ‘threat’ from the front, sides and rear, a ‘pressure zone’ forms in an oval shape based on movement of the individual player. A decay effect was incorporated into the model whereby pressure was at its highest level at the origin of the oval and decayed rapidly when moving away (Andrienko et al., 2017). The benefit of using an oval shape, is that whilst accounting for a different level of pressure from different directions, it also enables multiple pressure sources to be measured at once. Another method used to measure pressure was around based on the distance between both attacking and defending players and the ball (Taki, Hasegawa, & Fukumura, 1996). However, later research found this model to be too simplistic as the orientation of players was not included (Gudmundsson & Horton, 2017). Yet, orientation can be difficult to include as issues have also been encountered though the inability to reconstruct the directions of players from trajectory data (Andrienko et al., 2017). Other limitations have been found due to a focus on individual players, without accounting for the coordination and support of the team and their interaction with the opposition (Andrienko et al., 2017). Measures of pitch control or dominate regions begin to understand how space is occupied across the entire playing area, as well as the ball location (Fernández & Bornn, 2018; Nakanishi, Murakami, & Naruse, 2007; Taki & Hasegawa, 2000).

The interaction of attackers and defenders fluctuates to different magnitudes throughout a game. This may provide a measure of the variation between an attacker and defender dyad (Davids et al., 2012). This dyad is dynamic and is shaped by individual task and environmental constraints (Davids et al., 2012). The interaction between situational pressure and performance failure are reliable predictors of future performance failures (Harris, Vine, Eysenck, & Wilson, 2019). In a controlled environment, pressure can influence a closed skill, such as free throws in basketball. However, the influence of pressure on performance is dependent on the individual (Otten, 2009). Furthermore, pressure also varies based on external stimulus such as the score and time in the game. Within the applied setting coaches and analysts are often interested in how the intensity and pressure of a game fluctuates over time (Gudmundsson &

Horton, 2017; Sandholtz & Bornn, 2018). As such, it is important to explore the results of these dyads in the applied match setting and not just in a controlled environment.

As of yet, no common approach has been taken to qualitatively quantify pressure acts within sport. This is due to the unique nature of pressure and how it will affect individuals differently. Individuals respond and cope with pressure and anxiety differently (G. Jones, 2002). It is also important to note a pressure act may be different to continuous pressure, which fluctuates throughout a match. Ultimately, the goal of the defence is to apply pressure to win the ball back and/or deprive the opposition of scoring opportunities (Andrienko et al., 2017). Teams will alter their defensive pressure based on what they believe to be the opponent's weakness, for example, a team poor at retaining the ball may have a high-pressure tactic used against them (Gudmundsson & Horton, 2017). The intent and style of defence should be considered to quantify pressure.

Pressure can be quite difficult to quantifiably measure given the number of factors and differences individuals experience. Accordingly, the verification of a pressure metric is also difficult. No ground truth metric exists for the quantification of pressure (Andrienko et al., 2017). One method in soccer examined the number of unsuccessful passes, with the assumption that they have been unsuccessful due to the pressure being applied by the defence (Andrienko et al., 2017). Unsuccessful was defined as either a turnover, the ball going out of bounds or passing backwards. However, tactics limit the viability of these verification techniques. Research exploring pressure has assumed that attackers would be attempting to move the ball forward (Andrienko et al., 2017). However, this does not account for tactics such as swinging the ball or attempting to control momentum and flow by the offensive team. As such the validation model using this definition of an 'unsuccessful' pass may place too much credit on the defending side.

The interaction of constraints can be exemplified using pressure. Pressure is a complex concept which is difficult to measure due to individual, environmental and task constraints and their interaction. Individual constraints may include mental fortitude and levels of resilience. Environmental constraints may include playing at home or away. Finally, task constraints may include available space and time remaining. All of these constraints interact with one another to exert a level of pressure experienced by an individual. Thus, when exploring the concept of pressure, metrics should attempt to include dependent and independent factors to encompass pressure in its entirety. An understanding and consideration of constraint interaction can help analyse a complex system.

2.2.4 Challenges and Opportunities

Ecological dynamics has been explored extensively within the skill acquisition and physical education literature. Most research has been conducted in the laboratory or closed settings. Laboratory settings, which often involve a contrived task, can lead to findings surrounding behaviours and decision-making which may not transfer to the real-world as the skills being tested are not in the environment in which they will be applied (Araújo et al., 2006; Farrow & Robertson, 2017; A. M. Williams & Ford, 2009; Wulf & Shea, 2002). Few performance analysis studies have explored the use of a theoretical model in the applied setting (Farrow & Robertson, 2017; Handford et al., 1997). Moreover, this research has typically been conducted in a training setting, and the competition environment has yet to be fully assessed. This could be attributed to challenges in research outside of laboratory or closed environments, however opportunities exist to improve methodologies and therefore gain more insight.

The interaction of individual, environmental and task constraints during sport is difficult to measure. Individuals will experience discontinuous changes in performance due to differences in emotions, diet etc., which cannot yet be readily measured (Davids et al., 2012; Handford et al., 1997). Furthermore, individuals will learn from their experiences, thus will be developing and changing the way they approach a task (Davids et al., 2012). The manner in which constraints interact with one another is crucial to understand. However, it is difficult to isolate and understand the combined influence of constraints. Current analysis techniques are typically univariate and do not take a holistic approach to account for interaction between individual, environmental and task constraints. This reductionist approach has been an issue which has limited the use and generalisability of skill acquisition and is referred to as a reason for non-representative research (McLean et al., 2018; Pinder & Renshaw, 2019; Renshaw et al., 2010). Therefore, future research should consider a more holistic and complex approach to quantifying performance.

Theoretical frameworks are not typically applied within sport research. For instance, despite clear findings surrounding the home ground advantage, most research lacks a theoretical rationale to understand why this phenomenon occurs (José Gama et al., 2016). An ecological dynamics viewpoint could aid in understanding why venues may act as a strong environmental constraints and influence player behaviour and game outcome (José Gama et al., 2016). However, the limited viewpoint of additional constraints, such as scoreboard pressure and opposition ranking, may also influence team skill execution throughout a game. Accounting for more variables can make the application of a theoretical framework more difficult.

Theoretical frameworks have had issues being implemented in the applied setting. It can sometimes be difficult to understand academic language (Renshaw & Chow, 2018), and similarities between terminology can lead to phrases and frameworks being used incorrectly within the literature (Araújo et al., 2007). This confusion in terminology has created a barrier in the development and the conceptualisation around these theoretical frameworks (Renshaw & Chow, 2018). It has been suggested that difficult language and terminology has resulted in both a lack of understanding and misinterpretation of ideas and knowledge, which may have led to poor results when attempting to apply a CLA (Chow et al., 2007). This may cause further issues as it may create a negative perception of a CLA (Renshaw & Chow, 2018). Idyllically, the relationship between practitioners and researches would be more interdependent so that experiential learning could inform both research and practice (Renshaw et al., 2010; Rothwell et al., 2020; Woods, McKeown, Rothwell, et al., 2020). This could help in reducing the terminology barrier to the application of an ecological dynamics rationale.

The manipulation of constraints is often required for learning, and this needs to be carefully structured around the desired outcome. The need for a theoretical framework and the manipulation of constraints to be incorporated into training and learning environments has been suggested (Pinder et al., 2011; Renshaw et al., 2010). However, in true representative design, a greater understanding of the influence of these constraints at the match level is crucial to inform the appropriate manipulation of constraints, yet this remains to be fully examined. Furthermore, additional research is required to understand if the replication of the competition environment the most effective method to develop skills and transfer learning from training to competition. This is influenced by a large number of factors, such as individual learning traits, prior knowledge and further key sources of information which are maintained to guide individual actions and decisions, however, the influence of these factors is not yet understood from a quantitative perspective. Future research should seek to understand what leads and causes transfer of learning effectively.

2.2.5 Conclusion

Skill acquisition can be achieved with an ecological approach to the learning and development of skills. An ecological approach can enhance the transfer of skill development, as it is proposed to provide benefit by experiencing competition-like environments in training (Guerin & Kunkle, 2004; Renshaw et al., 2010). For a study to be representative, individuals need to be able to interact with environmental constraints in training that are similar to the competition environment (Brunswik, 1956; Davids et al., 2006). An increased understanding of individual, environmental and task constraints and their subsequent interaction and influence in competition may allow for an improved and more representative practice setting. However, research needs to be continued as constraints are dynamic and their influence can alter over time (Guerin & Kunkle, 2004; Renshaw et al., 2010). Viewed from a non-linear pedagogical and ecological dynamics perspective, the change and decay of constraint influence demonstrates that constraints act dynamically and should not be viewed statically as discrete events. Ecological dynamics can provide an in-depth conceptual framework to aid the implementation of analytical measures by practitioners and coaches (Araújo & Davids, 2016). Future research needs to, acknowledge constraints and their influence on performance, and also adjust analysis techniques to account for constraint interaction. Future research should consider a theoretical framework to better understand the complexity of sport to help quantify performance.

2.3 Analysis Techniques

Data and data analysis form a fundamental part of research. The collection of data can lead to the generation of information and new insights. Data can take many forms, from numerical, figures and text documents, through to more complex data types such as spatial, multimedia or hypertext documents (Deshpande & Thakare, 2010). However, the collection of data itself does not provide insight, this comes from the extraction of essential information and the discovery of patterns within the raw data. The discovery of patterns and knowledge from large datasets has been referred to as data mining (Lavrač, Kononenko, Keravnou, Kukar, & Zupan, 1998).

Data mining has been defined as the science and technology of data exploration with the aim to discover unknown patterns to uncover knowledge and generate useful information about a database (Deshpande & Thakare, 2010; Friedman, Hastie, & Tibshirani, 2001; Gupta, Rawat, Jain, Arora, & Dhami, 2017; Larose & Larose, 2014). Data mining can be used to objectively predict future trends and behaviours, which can allow decision-makers to be proactive with knowledge-based decisions (Deshpande & Thakare, 2010; Larose & Larose, 2014). Numerous techniques, technologies and applications surrounding big data are applied to aid business understanding and timely decision-making (Galetsi, Katsaliaki, & Kumar, 2020). The application of data mining has moved beyond business into the healthcare sector and the sporting domain (Couceiro et al., 2016; Galetsi et al., 2020). Within sport, data which describes a player's performance is growing, as such data mining methods are becoming an increasing useful tool to analyse large datasets (Wenninger, Link, & Lames, 2019).

Machine learning refers to computer systems which can learn from data without being explicitly instructed or programmed and unveil meaningful patterns within a dataset (Herold et al., 2019; James, Witten, Hastie, & Tibshirani, 2013). These algorithms are essentially a sequence of instructions which model a function to produce an output from the data input. A model aims to improve the parameters assigned to enhance the discovery of patterns within a dataset (Deisenroth, Faisal, & Ong, 2020). Machine learning has been used across a number of fields to retrieve and analyse information around data, video and speech recognition (S. Liu, Wang, Liu, & Zhu, 2017). These data sources are becoming more common in sport.

Machine learning can be differentiated from data mining by its emphasis on developing accurate and predictive models. In comparison, data mining emphasises the discovery of new information and insights in databases. A further benefit of machine learning is the ability to refine models through the incorporation of gained knowledge (S. Liu et al., 2017). Computational models can be applied across a range of fields including sport. Machine learning offers the ability to conduct quantitative analysis beyond the scope of traditional observation-based analysis techniques through being able to deal with different distributions and non-linear analysis (Herold et al., 2019). Extracting in-depth detail from large datasets is reliant upon data mining and machine learning techniques. Complex algorithms and probabilistic analysis provide tools to gain information from object trajectory and match event data (Gudmundsson & Horton, 2017). Differences exist between machine learning and data mining; however, both provide techniques to understand sporting performance.

Machine learning can be categorised into three main approaches: supervised, unsupervised, and reinforcement learning (Figure 2.2) (Géron, 2019; Mohammed, Khan, & Bashier, 2016). A supervised algorithm would attempt to match patterns within the dataset to prior examples. In contrast to this, an unsupervised approach searches for latent patterns, where the algorithm has no preconceived notion about which rules or patterns should be considered correct. Within these two types of machine learning, more technique specific areas exist; i.e., regression, classification, rule-based, clustering algorithms and anomaly detection (Deshpande & Thakare, 2010; Gupta et al., 2017; Witten, Frank, Hall, & Pal, 2016). A learning problem could fall between these two approaches, this is referred to as semi-supervised (Chapelle, Weston, & Schölkopf, 2003). Finally, reinforcement learning is an approach where the training environment trains on data continuously throughout a trial and error process (Sutton, 1992). These machine learning categories are defined by the data available and the research question being proposed.

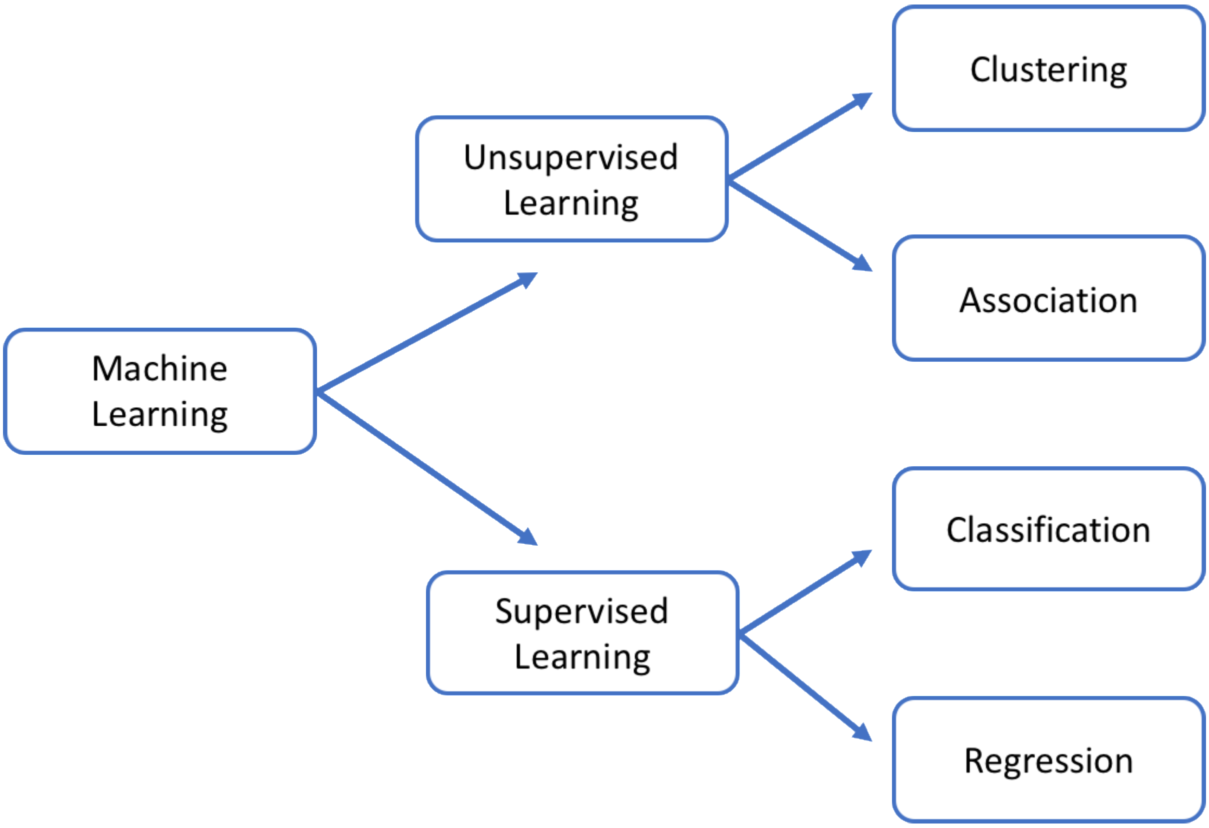

Figure 2.2 Breakdown of machine learning techniques. Adapted from Mathworks (2020).

As sports technology has improved, so too has the data available. Accordingly, sport is an ideal industry to utilise data mining and machine learning techniques (Deshpande & Thakare, 2010). Machine learning can inform practitioners around statistical analysis, frequent patterns and pattern discovery (Browne, Morgan, et al., 2019), as well as predicting events (Cervone et al., 2014; Pocock et al., 2018) and match outcomes (Cervone et al., 2014; Deshpande & Thakare, 2010). Improved analytical methodologies allow for more complex issues, such as the interaction of players, to be measured (Benito Santos, Theron, Losada, Sampaio, & Lago-Peñas, 2018; Gudmundsson & Horton, 2017). Accordingly, the statistical approaches applied are an important aspect of performance analysis (Robertson, Back, et al., 2016). In recent times have statistical approaches been more readily utilised to inform the decision-making processes (Sicilia et al., 2019). Many methods and approaches have been attempted in this area, such as different linear techniques including discriminant analysis (Castellano et al., 2012), generalised linear modelling (Higham, Hopkins, Pyne, & Anson, 2014) and multiple regression techniques (Stewart et al., 2007). These techniques enable more variables and constraints to be explored in sporting environments to improve the decision-making process.

Given the complex nature of team invasion sports, non-linear machine learning techniques are becoming more prevalent through their ability to account for and identify numerous patterns within complex data (Bunker & Thabtah, 2019; Dutt-Mazumder, Button, Robins, & Bartlett, 2011; Haghighat, Rastegari, & Nourafza, 2013; Robertson, Back, et al., 2016). Bayesian statistical methods have been used across numerous individual and team sports to model and analyse performance (Santos-Fernandez et al., 2019). For example, in basketball logit multinominal Bayesian regressions have been used to understand the relationship between shot location and additional variables such as the presence of teammates and opposition as well as whether the game was at home or away (Reich et al., 2006). This approach to conducting a spatial analysis of shot charts enables multiple variables to be analysed. Furthermore, it is not limited to two regions as in an ordinary logistic regression (Reich et al., 2006). It also enables smoothing between bins based on location. This would not be possible if using a simple frequency count of shot and outcome by bin location. Other approaches such as neural networks, decision trees and cluster analysis have been applied in the sporting domain to understand performance from a complex and more inclusive perspective (S. Morgan et al., 2013; Silva et al., 2007; Sweeting, 2017). Whilst increasing the amount of data aids in improving model accuracy, the improvement typically plateaus at a certain point (Witten et al., 2016).

Machine learning methods have been demonstrated to produce effective models. These methods often have the benefit of being unconstrained to a single linear function and therefore allowing the ability to potentially identify multiple underlying patterns within the data (Back, 2015; Dutt-Mazumder et al., 2011). However, poor experimental design and inappropriate selection of the dependent variables has meant that the true magnitude of effect from treatments or interventions may not be fully understood (Atkinson & Nevill, 2001). Thus, improvements in model design and practitioner education are required to aid the transfer of machine learning into the applied sport setting. One solution may be to utilise a combination of expert opinion alongside practitioners to design and interpret a model as part of a mixed initiative guidance to improve a machine learning model (S. Liu et al., 2017). Although this mixed initiative guidance can improve output, it is very technically demanding which reduces the feasibility of such an approach (S. Liu et al., 2017).

Statistical techniques and computer science have not been used to their full potential in the sporting industry. More research should be conducted with the use of machine learning in sport to improve tactical and performance knowledge (Herold et al., 2019). In sport, the use of machine learning techniques can account for complex environments, but can also be daunting for practitioners new to the area to implement due to the stigma of incomprehensible functions, terminology and the “black box” nature of many techniques (S. Liu et al., 2017; Robertson, 2020). This may also be due to potential misunderstanding surrounding the use of these techniques and lack of explanation on why and how these systems work (Kayande, De Bruyn, Lilien, Rangaswamy, & Van Bruggen, 2009; S. Liu et al., 2017; Robertson, 2020). This means that when these models are produced, they may fail to be implemented due to their inability to convey information and aid decision-making as the way the model operates is not fully understood (S. Liu et al., 2017). If this stigma can be overcome and the techniques used correctly, data mining and statistical modelling provides a method to uncover new insights and derive meaning in previously data-rich and information-poor areas (S. Morgan et al., 2013). Machine learning can greatly aid the implementation of an ecological dynamics theoretical framework to performance analysis as it enables the analysis of these complex situations (Buekers et al., 2017). Outlined in the following subsections are different statistical models and machine learning techniques used within this thesis (Chapters Three to Six).

2.3.1 Logistic Regression

The use of statistical models to explain categorical choices is a common approach in computer science (Kasap, Ekmekci, & Ketenci, 2016). Logit models are frequently used across a range of fields, such as medicine and social sciences, due to their relatively easy application and ability for results to be understood (Kasap et al., 2016; Peng, Lee, & Ingersoll, 2002). Within logit analysis, the aim of the technique is to represent the relationships between dependent and independent variables and to find the best fit among them (Kasap et al., 2016).

Logistic regression is a mathematical modelling technique which is used to describe the relationship of several independent variables to a dependent variable (Atkinson & Nevill, 2001). It was originally proposed as an alternative to ordinary least squares regression and linear discriminate function analysis due to its ability to handle dichotomous outcomes (Peng et al., 2002). First proposed in the 1960's, logistic regressions then became common statistical packages in the early 1980s (Peng et al., 2002). The calculation of coefficients from a logistic regression is more complex than can be efficiently performed through traditional methods (Bagley, White, & Golomb, 2001). Thus, statistical software packages have made running logistic regression models more feasible (Bagley et al., 2001). Specifically, logistic regressions aim to explain differences in the dependent variable in relation to changes which occur with the independent variables (Draper & Smith, 1998).

Logistic regressions are widely used for the identification of variables which relate to sports performance, when working with a dichotomous dependent variable (Atkinson & Nevill, 2001). Logistic regressions are typically used to model multivariable methods with dichotomous outcomes (Bagley et al., 2001). For instance, logistic regression models have been developed to understand the relationship between variables such as location, individual history and match context (independent variables) and the binary shot outcome, goal or no goal (dependent variable) (Pocock et al., 2018). A logistic regression model may therefore be applied where a hypothesis exists for the relationship between a outcome categorical variable and predictor variables (Peng et al., 2002). The relationship between variables can be measured through an odds ratio. The odds ratio is derived from two odds, the regression coefficients in a logistic model. The odds ratio provides a measure of association between the independent and dependent variable (Szumilas, 2010). This value is the regression coefficient of the predictor in a logistic regression (Peng et al., 2002).

Regression models have been used extensively within team sport analysis. For instance, logistic regressions have been used to determine an the estimated effect of an individual on a team's scoring performance in ice hockey (Gramacy, Jensen, & Taddy, 2013). Alternatively, in basketball, regressions have been used to classify combinations of performance indicators which could explain match outcome (Leicht, Gomez, & Woods, 2017). Within AF, a logistic regression was applied to understand injury risk factors (Orchard, Seward, McGivern, & Hood, 2001), measure training load (Veugelers, Young, Fahrner, & Harvey, 2016) and identify talent and development (Robertson, Woods, & Gastin, 2015; Woods, Raynor, Bruce, McDonald, & Collier, 2015). The practical applications of these papers could be to optimise player matchups, devise team strategies and determine player value. However, the application of logistic regressions in the applied setting has limitations.

Whilst logistic regressions are effective, they do have their limitations. Feature engineering is an important aspect of this technique as the inclusion of variables which are highly correlated, and therefore can lead to problems with estimation (Bewick, Cheek, & Ball, 2005). Logistic regression also requires a large sample size, which is often difficult to obtain given the nature of sport (Bewick et al., 2005). Logistic regressions cannot be used to solve non-linear problems. This is a major limitation given the use in sport, the regression is attempting to be used to analysis a complex non-linear environment. Furthermore, the outcome is discrete, thus it can only predict a categorical outcome. They provide insight into each individual variable, however when analysing a complex system, such as sport, applying logistic regressions to understand the nexus of variables or constraints is not the most effective analysis technique.

2.3.2 Decision Trees

The most widely used supervised classification techniques are decision trees (Gupta et al., 2017). Decision trees are diverse in nature and can be used for both linear and non-linear analysis, for regression or classification problems and have the ability to handle both categorical and continuous data (Gupta et al., 2017). A decision tree establish a hierarchical solution to classification problems, in that a set of rules can be derived based on the interaction between variables in a dataset (S. Morgan et al., 2013).

Divides or branches occur in the tree to form mutually exclusive subsets which can best describe the dependent variable. Each branch represents a rule, and a branch is formed by the splitting of a variable to discriminate between states of a binary dependent variable (S. Morgan et al., 2013). Therefore, each split forms two new branches, which may then split again or not depending on the dependent variable and the parameters set (Figure 2.3). Accordingly, decision trees are described as recursive-partitioning models (S. Morgan et al., 2013). This action of splitting branches continues until the model is unable to form any further splits based on the set parameters (S. Morgan et al., 2013). Decision trees are typically applied on large, highly dimensioned data datasets and are insensitive to missing data (Han, Kamber, & Pei, 2012). A major benefit of decision trees is the ease of use and understandable output due to the rule like nature (Hajizadeh, Ardakani, & Shahrabi, 2010; S. Morgan et al., 2013). Yet, they are susceptible to over-fitting, and thus caution should be taken when training a decision tree (S. Morgan et al., 2013). Over-fitting occurs when a trained model has been designed too specifically to the features of a training dataset, and therefore may fail to predict future observations from a different dataset accurately (Rokach & Maimon, 2008; Schelling & Robertson, 2020).

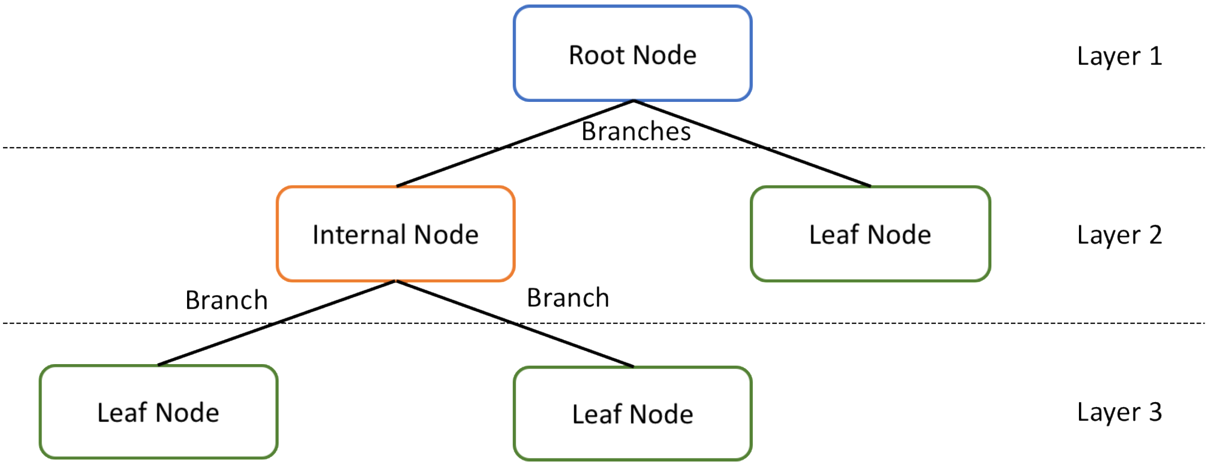

Figure 2.3 Basic structure of a decision tree (Chiu, Yu, Liaw, & Chun-Hao, 2016).

2.3.2.1 Conditional Inference Trees

Conditional inference trees improve the statistical approach to recursive partitioning whilst taking into account measures of distributional properties (Hothorn, Hornik, & Zeileis, 2015; S. Wang et al., 2018). Conditional inference trees are a supervised machine learning technique which consist of a range of significance tests that determine a threshold for each dependent variable (Corbett et al., 2017; Sarda-Espinosa, Subbiah, & Bartz-Beielstein, 2017). They offer a technique well suited to both explanation and predication problems (Hothorn, Hornik, & Zeileis, 2006). Conditional inference trees have been developed from other automated interaction detection decision tree algorithms (Hothorn et al., 2006; J. N. Morgan & Sonquist, 1963). The accuracy of conditional inference trees is subject to the best splitting criteria being selected, meaning the accuracy of the model is subject to user error. The benefit of conditional inference trees is that they overcome issues surrounding overfitting and selection bias through statistical test procedures to variable selection and stopping criteria (S. Wang et al., 2018). Furthermore, they provide a non-linear approach to quantify the relationship between dependent variables (Corbett et al., 2017). Branches consists of different combination of response variables, such as the outcome of a shot on goal, which leads to the prediction of the independent variable (Corbett et al., 2017). Thus, a conditional inference tree may enable a coach or key stakeholder to understand how an event, in this case a shot on goal, is influenced by a number of factors, such as pressure, distance, angle and kick type.

Conditional inference trees have been used in a range of research areas. For instance, to analyse the reliability of automobile engines (S. Wang et al., 2018) and in sport research to provide an understanding of the relationship between risk factors in snow sports to improve training design (Hasler et al., 2010). In AF, conditional inference trees have been used to explore the relationship between playing time between rotations, physical and skilled outputs in AF (Corbett et al., 2017). This information could better inform planning for rotations for individual and team success (Corbett et al., 2017).

2.3.3 Association Rules

2.3.3.1 Traditional (Apriori)

A rule-based approach is a research method for discovering interesting relationships or correlations between variables in large datasets (Hajizadeh et al., 2010). It is a branch of machine learning which identifies frequently occurring patterns within large transactional datasets (Agrawal & Srikant, 1994; Goh & Ang, 2007). Information surrounding frequent sets are generally used to extract association rules, to demonstrate how a subset of items within a itemset influences the presence of other items within the transactional database (Perego, Orlando, & Palmerini, 2001). Database literature has typically focused on developing algorithms that identify conjunctive rules which meet user-specified parameters such as minimum confidence, support and lift (Bayardo, Agrawal, & Gunopulos, 2000).

Association rules became popularised in 1993, with the AIS algorithm (Agrawal & Srikant, 1994; Kasap et al., 2016). However, this style of algorithm was originally proposed in 1966 as the GUHA algorithm (Hájek, Havel, & Chytil, 1966). The Apriori algorithm has been the most used algorithm in the field, however many other algorithms such as FP-Growth and Eclat are used (Han, Pei, Yin, & Mao, 2004; Kasap et al., 2016; Zaki, 2000). Association rules have been predominately affiliated with its early applied origins of a 'market-basket analysis', where retail businesses explored combinations of purchases made by customers. For instance, a set of items bought together at a supermarket such as bread, butter and eggs, combined with other information such as date, customer profile and location, could offer insight into consumer spending and preferences (Cariñena, 2014; B. Liu, Ma, & Wong, 2001; Perego et al., 2001; Robertson et al., 2019). Association rules have also been applied extensively across a number of fields from marketing and finance to medical diagnosis and sport (Anand, Patrick, Hughes, & Bell, 1998; Goh & Ang, 2007; S. Morgan, 2011; Robertson et al., 2019; Sanz et al., 2014).

The Apriori algorithm is a method of unsupervised machine learning which can generate association rules. The latent patterns are generated based on search parameters, such as support and confidence, without being able to match results with prior examples or a template. Developed by Agrawal and Srikant (1994), they allow for the identification of associative trends in a dataset. The basis of an association rule can be demonstrated in a simple formula:

$$A \Rightarrow B \qquad \textit{Equation 1}$$

Where A and B represent item sets, and the implication symbol (=>) represents that when a combination of item sets meets the conditions in A, it will also satisfy the conditions of B. In this association rules take the form of antecedent => consequent (Kliegr & Kuchar, 2019). The dataset is scanned to count the level of support for each itemset. This provides a set of non-empty frequent L-itemset, L_1 (large frequent itemset 1), this is then used to find L_2 (large frequent itemset 2), and L_3, until all candidates are found (Figure 2.4) (Browne, Morgan, et al., 2019).

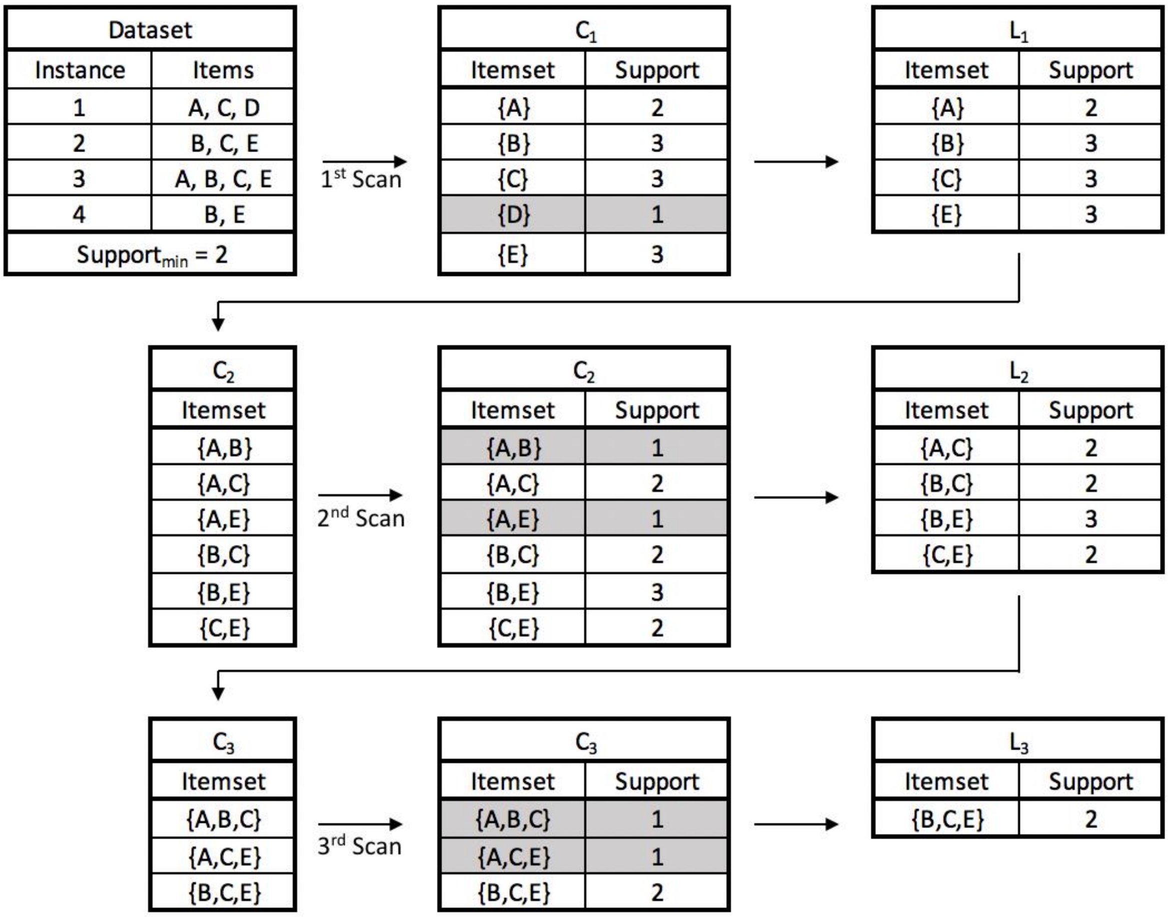

Figure 2.4 Tabular example of the Apriori algorithm. Where C_k is representative of the current itemset of size k; L_k is representative of the frequent itemsets of size k. The greyed rows represent rows which did not meet levels of minimum support, and therefore do not progress.

An association rule can be measured in terms of support, confidence and lift. Support is the number or proportion of results that contain both the antecedent and consequent in the database (Equation 2). Confidence is the measure of the ratio of the support of the rule to the support of the consequent (i.e., how frequently the items in the consequent occur in transactions containing the antecedent) (Equation 3). Lift refers to the confidence of the rule divided by the probability of the rule containing the consequent (Equation 4) (Zheng, Kohavi, & Mason, 2001). Typically, good rules will seek to have high support, high confidence and high lift. However, realistically, these are all interrelated and trade-offs may occur (Zheng et al., 2001).

$$support(A => B) = P(A \cup B) \qquad \textit{Equation 2}$$

$$confidence(A => B) = \frac{support(A \cup B)}{support(A)} = P(B|A) \qquad \textit{Equation 3}$$

$$lift(A => B) = \frac{P(B|A)}{P(B)} \qquad \textit{Equation 4}$$

Association rules have been used across a number of sports to identify frequent patterns in play. The Apriori algorithm was used to generate rules describing co-occurring ball movement patterns in field hockey (S. Morgan, 2011; Stöckl & Morgan, 2013). A study by Stöckl and Morgan (2013) explored women's hockey at the 2008 Beijing Olympic Games to discover the most common spatial trends. This study drew inferences around ball movement patterns and identifying which passages of play resulted in scoring opportunities (Stöckl & Morgan, 2013). Furthermore, pattern discovery has been used in order to identify common winning tactics and predictive measures in tennis (Terroba, Kosters, & Vis, 2010; Wei et al., 2013). Association rules have also been used to understand common passing patterns in netball (Browne, Morgan, et al., 2019). Additionally, a rule-based approach has been applied in AF to understand the influence of constraints on field kicking performance (Robertson et al., 2019). Whilst these studies have indicated the benefits of association rules, this technique also has some negative characteristics. Three main issues with association rules have been identified (Moreno, Segrera, & López, 2005): i) a propensity to output non-interesting rules, ii) discovered tendency to output a large number of rules and; iii) low algorithm performance in terms of simplicity and output (Moreno et al., 2005). For example, in hockey frequent patterns represented less than 2% of all occurrences in a dataset, potentially presenting non-interesting rules. However, this was justified as they were in actuality, more frequent when compared to the number of random events that occur in a match (S. Morgan, 2011). Whilst these rules may seem non-interesting or weak, with frequent patterns accounting for less than 2% of the dataset, the algorithm is seeking patterns which occur with co-existing features and which may not be apparent to the human observer. After all, if a pattern were very frequent it would be more easily identified by a human observer, and thus easier to coach against. Thus, association rules can be utilised in sport to identify frequent patterns within noisy data.

A major benefit of association rules is the relatively light mathematical concepts which make it easier to understand and interpret (Wenninger et al., 2019). Furthermore, due to the unsupervised nature of rule-based approaches they require less data preparation and feature engineering compared to other machine learning techniques (Wenninger et al., 2019). A limitation of association rules generated through the Apriori algorithm is that it does not account for the minimum importance of a constraint. In that it mines all rules, as opposed to those with confidence at least greater than the confidence of any of its sub rules (Bayardo et al., 2000). Thus, when applying association rules, it is important to account for lift to provide context to the predictive advantage of rules instead of guessing based on the frequency that the outcome occurs. Association rules provide a multivariate method which can be applied in sports performance research.

2.3.3.2 Classification Based on Association rules

The Classification Based on Association rules (CBA) algorithm, is an unsupervised data mining technique, which finds co-occurring items in large datasets to detect frequent patterns (Gentleman & Carey, 2008). Where traditional association rules provide a summary of what has occurred, CBA aims to include a predictive nature. They have been developed to improve the search to generate rules which meet the parameters set (B. Liu et al., 2001). The main strength of the CBA is its ability to use the most accurate rules for classification (B. Liu et al., 2001). The CBA uses a simple, but fast, method for sorting and removing superfluous rules (Kliegr & Kuchar, 2019). The main weakness of CBA is that only one minimum support can be used which can be inadequate for an unbalanced class distribution, as well as the management of large data with many conditions (B. Liu et al., 2001). Rule sets within CBA are built in a greedy manner to uncover as many rules as possible. These are also subject to the maximum number of variables allowed in the antecedent, which can limit the combinations of rules possible (Kliegr & Kuchar, 2019).

2.3.3.3 Fuzzy Association Rules

Fuzzy logic has been widely used in decision support systems. It is known for being able to produce simple and direct solutions to inform users (Ho, Ip, Wu, & Tse, 2012). Fuzzy logic has been widely applied in non-sporting industries to manage non-linear, multivariate control problems (Hoch et al., 2017). It is here that fuzzy logic has been seen to have an advantage over methods such as neural networks, association rules and genetic algorithms (Ho et al., 2012). The interpretability of a fuzzy system relies on the following traits. Firstly, the fuzzy partitioning for an input variable should be whole, and subsets should be unique (Jang & Sun, 1993; Jin, Von Seelen, & Sendhoff, 1998). Secondly, the number of subsets should be limited and each subset should contain a unique membership function (Jin et al., 1998). Thirdly, fuzzy rules should be consistent within the rule base (Jin et al., 1998; Jin, Von Seelen, & Sendhoff, 1999; L.-X. Wang & Mendel, 1992). Finally, the number of rules within a fuzzy system should be as small as possible (Jin et al., 1998). Fuzzy logic can be applied for IF-THEN rules for characterizing events, this is particularly usefully for the beginning and end of temporal phase events (Hoch et al., 2017). This technique can be readily incorporated to applied problems.

An integrated approach between association rules and fuzzy time series has been used to create a model surrounding the forecasting of events (H.-T. Liu, 2009). This could be useful in the analysis of match events in sport to understand not only their sequencing, but also the temporal nature in which they occur. The ability to be able to integrate fuzziness within a rule-based approach may help account for the limitation of association rules in quantitative data analysis (Ho et al., 2012). This combined technique has been used to analyse the stock market to uncover interesting patterns resulting from interplaying attributes between the stock market and the larger economy (Ho et al., 2012). It has also been used to create a model which can greatly reduce the risks involved in the stock market through a decision support system (Ho et al., 2012). This can also be applied to sport to help understand how time influences aspects of performance. Further to analysing match events, understanding fixturing and team development could be explored. In rugby, performance has been measured using four separate scenarios of pre-defined number of weeks (Robertson & Joyce, 2018). A fuzzy approach could be used to demonstrate that this window is not as well defined. A fuzzy approach may be more effective at predicting performance outcomes as well as reducing the need to analyse four scenarios. Problems surrounding completeness and consistency with fuzzy rule systems can occur. These problems can be managed using completeness and consistency indices which have been proposed and integrated into the cost function of the evolutionary algorithm (Jin et al., 1998). Being able to understand the association between different variables through a fuzzy approach may aid in informing practitioner decision-making in the applied setting.

2.3.4 Decision Support Systems

A decision-support system (DSS) is a computer-based system designed to provide objective evidence to aid decision-making (Sprague Jr, 1980). A DSS can be used across numerous fields to evaluate individual and team health, performance and other factors. Whilst the concepts of a DSS seem logical, their interpretation and application depends greatly on the context within which the decision is being made (Bohanec, 2003). These systems are typically computer-based information systems which can aid in informing objective decision-making (Robertson, Bartlett, & Gastin, 2017). A DSS uses historical data to form a recommendation or provide an assessment to the user, typically based on a software-based algorithm (Robertson et al., 2017). They have evolved from multiple areas of research, the main being organisational decision-making (Shim et al., 2002), and are now applied across multiple domains including sport (Robertson et al., 2017; Schelling & Robertson, 2020; Zeleznikow, MacMahon, & Barnett, 2009).

Within sport, a DSS has been used to evaluate aspects of player performance, aid athlete selection and facilitate the scheduling of tournaments (Calder & Durbach, 2015; Kawamoto, Houlihan, Balas, & Lobach, 2005; Kostuk & Willoughby, 2012; Robertson et al., 2017). A DSS can range from data displays, statistical analysis, modelling and graphs which are generated to aid human judgment and inform decision-making (Silver, 1991). For a DSS to be used effectively, it is important that decision makers are willing to use the system and make changes and judgements based off the findings (Hunt, Haynes, Hanna, & Smith, 1998; McIntosh et al., 2019; Robertson et al., 2017). Therefore, an evidence-based practice demonstrating the benefit of a DSS is required for key stakeholders to have confidence in using the system (Fullagar, McCall, et al., 2019). The feasibility of a DSS depends on how it aligns with five key factors which relate to its quality and potential impact (Robertson et al., 2017). These critical factors are: burden, cost, time, interpret and measure (Robertson et al., 2017). The integration of data is critical as the need to increase the transparency surrounding data and findings has received more attention in recent times (Robertson et al., 2017). This has become more relevant in sport with the increased availability of data.

The application of concepts such as bounded rationality and parsimony could aid the design of a DSS. Bounded rationality refers to the concept in which rational decision-makers are bound to make simple, satisfactory choices, rather than maximizing or optimising their decisions

(João Gama, 2013; Gigerenzer & Selten, 2002; Robertson & Joyce, 2019). This is due to the concept of rationality being constantly bounded by the interaction of both cognitive and environmental constraints (Robertson & Joyce, 2019; Simon, 1956). The theory of bounded rationality can help to explain how two individuals faced with the same problem can arrive at different solutions, even when having access to the same information on which decision-making can be based (Robertson & Joyce, 2019). Parsimony explores the concept of finding the appropriate balance between collecting too little and too much information to sufficiently inform the evaluation of a problem. Too much information being collected may only provide a small insufficient improvement to the assessment without really aiding the decision-making process, whilst requiring additional resources (Robertson & Joyce, 2019; Schelling & Robertson, 2020). One principle of parsimony centres around Occam's razor, where "entities should not be multiplied unnecessarily" and an attempt to take the simplest solution should be made (Efatmaneshnik & Ryan, 2016). The analytical approaches most appropriate for problem solving depend on the efficacy of a solution, but are also dependent on how well it aligns with standard operational processes (Robertson, 2019). If a DSS could be integrated within a sporting team environment it may help coaches and other key stakeholders implement data and findings more efficiently.

Feedback and reports to coaches should be provided to in an appropriate manner for improved performance (Liebermann et al., 2002; Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2018). Feedback can be almost instantaneous when using improved technology (Liebermann et al., 2002). This improvement has led to many practitioners considering the information collected from improved technology to be invaluable (Liebermann et al., 2002). Implementing tools such as visual feedback can inherently provide information about the individual and environment are interacting (Liebermann et al., 2002). Understanding this relationship can aid in training design and improving skill motor learning (Pinder et al., 2011). However, the increase in available technology, data and analysis has not led to a linear improvement in performance

(Couceiro et al., 2016). It is important that whilst these technological improvements are happening, the ability for results to be easily interpreted within the applied setting is a crucial element of the feasibility of the technology. The visualisation of data is crucial to the successful application of the data findings (Lavrač et al., 1998). For instance, GPS data is often reported as discretised numbers in a table, however it could be presented visually alongside match event data, to help make the data and information more accessible for practitioners.

2.3.5 Visualisations

Analysis techniques and a DSS need to be appropriately communicated in order to be applied by practitioners. Visualisations provide a tool to aid this communication. Visualisations balance on the boundary of being a science and an art (Ware, 2019). The science behind visualisations can be explored through the perceptual sciences, which refers broadly to the integration of neuroscience, computer science and psychology with the aim to understand the link between external properties and cognition (Goldstone, 1998; Green, 1998). Cognitive science is the interdisciplinary study of the processes within the mind and how they work (Thagard, 1996). Together, the elements of cognitive science demonstrate how the science and language of visualisations can be used to improve the communication of complex phenomena in sport. In doing so visualisations may support the comprehension of findings and could lead to improved decision-making. The impact of visualisations on stakeholder decision-making has been examined in forecasting, communication and planning (Fagerlin, Zikmund-Fisher, & Ubel, 2011; Fernandes, Walls, Munson, Hullman, & Kay, 2018; Padilla, Creem-Regehr, & Thompson, 2019; Padilla, Ruginski, & Creem-Regehr, 2017). Data visualisation has the ability to help make a message more persuasive and more readily adopted. Publications such as the New York Times and The Guardian have popularised the use of visualisations to tell a story and provide a message, and this has continued into business and research (Pandey, Manivannan, Nov, Satterthwaite, & Bertini, 2014).

A foundational study for information visualisation occurred in 1984 (Cleveland & McGill, 1984). This study explored the basic perceptual tasks performed when perceiving a graph, and found that it is easiest to compare items along a common scale (Cleveland & McGill, 1984). Visualisations use two key principles to convey information: i) reductionism and, ii) the use of spatial variables (Manovich, 2011). Reduction reflects how points, lines and other geometric shapes are used to represent objects and relations between them (Manovich, 2011). Spatial variables are used to represent distinct differences within the analysis and reflect the key patterns and relationships (Manovich, 2011). Visualisations offer the ability to manipulate other factors such as data point size, hue, shape, alongside data being presented on two axes. Thus, visualisations offer a simple way for five dimensions to be easily manipulated to help convey a message. Therefore, visualisations can aid in conveying the interaction of multiple variables in one visualisation, which if alternatively presented in a table could be make the interaction between variables more difficult to comprehend.

Visualisations have been proposed as a method to leverage data communication to clearly highlight findings with precision and efficiency. The transition from data and analysis to the creation of a visualisation may aid in the uptake of information and thus, insight into the applied setting (Green, 1998). This is required in sport as, despite improvements in technology and analytics, a linear improvement in performance has not occurred (Couceiro et al., 2016). This is potentially a result of the difficulty of gaining insights from numerical data (Green, 1998; Kale, Nguyen, Kay, & Hullman, 2018). Moreover, it may require an increased cognitive load to comprehend tables compared with visualisations (Green, 1998; Kale et al., 2018). Tables, however, may be useful when interpreting absolute values (Spence & Lewandowsky, 1991). Visualisations provide a tool to translate numbers into a simpler medium (Green, 1998). Applied analytical methods need to be accessible and understandable for practitioners, and visualisations can aid this. Visualisations may be better able to meet user experience demands (Padilla, Kay, & Hullman, 2020) by improving engagement and enjoyment (Pinker, 1990), memorability (Fagerlin, Wang, & Ubel, 2005), user speed, accuracy and cognitive load (Padilla, Castro, Quinan, Ruginski, & Creem-Regehr, 2019). Ultimately, if reporting methods are not interpretable or operational, the best performing model will not be implemented by key stakeholders in the applied setting, (S. Liu et al., 2017; Robertson, 2019).

Some limitations exist with the use of visualisations. Biases are cognitions which prejudice and distort processing of information and decision-making (Arnott, 2006). Biases may be present in visualisations. For instance, the layout and design of a graph can lead to a user believing lines are more similar than they actually are or causing two charts to appear more symmetrical based on their design (Jordan & Schiano, 1986; Schiano & Tversky, 1992; Tversky & Schiano, 1989). Moreover, the number of components displayed in a graph can impact the user's understanding. For example, as the number of components displayed in a bar chart increases, the effectiveness of the graph may decrease (Hollands & Spence, 1998). Uncertainty in visuals can arise from a number of factors, such as variability within a sample population, computational and knowledge limitations (van der Bles et al., 2019). Furthermore, whilst bias exists with some visualisations, visuals can also be a poor tool to display proportional data (Spence & Lewandowsky, 1991). Hence, the selection of an appropriate visualisation is important, as well as not over complicating the visual. An example of this is in the use of pie charts, which the value of has been debate for close to a century (Eells, 1926). Pie charts are negatively viewed in the literature, as users judge the size of an area less accurately compared to when the same information displayed with the length of a line in a bar graph (Spence & Lewandowsky, 1991). Additionally, caution should be used with visualisations, as whilst they may make a report more persuasive, that does not necessarily mean the report is more accurate. The inclusion of a visual in an academic paper has been found to increase public persuasion, despite the visual in this experiment not accurately reflecting scientific rigour (Tal & Wansink, 2016). These limitations mean that sometimes a properly constructed table may be superior to a visualisation, however this is dependent on the message being conveyed, the user and appropriateness of the visual (Ehrenberg, 1975; Tufte & Graves-Morris, 1983).

An effective visualisation is dependent on a balance being found between the science and art of a visual. In the applied setting visuals need to convey information quickly and with simplicity for maximal comprehension. Visualisations have the ability to convey complex information, but this needs to be done in a manner which a practitioner can quickly view, assess and gain insight efficiently from the visual. Implementing the findings from foundational perceptual science research can help to encourage this simplicity and also the selection of an appropriate visual (Zacks & Tversky, 1999). Visualisations are critical as, irrespective of the aptitude of a model or analysis techniques, the implementation of the information provided is dependent on the human user.

2.3.6 Conclusion

Data is fundamental to research and can lead to the generation of new insights. However, the collection of data itself does not provide insight, this comes from the extraction of essential information and the discovery of patterns within the data. Methodologies that can include multiple variables can better account for the inherent properties which exist within complex systems (Ribeiro et al., 2019). Data mining and machine learning techniques offer various insights and methods to analysis data whilst accounting for this complexity. This thesis focusses on the application of logistic regressions, conditional inference trees and rule-based approaches in AF. An improvement in the application of multivariate analysis techniques is required with the concurrent increase in availability of data. Furthermore, the use of a DSS and visualisations may aid the implementation of analysis in the applied setting.

2.4 Section Summary

Sport is complex and the application of quantitative analysis is growing (McHale & Relton, 2018). Performance analysis has been posited to help quantify and generate findings from data. The insights gained from performance analysis are varied. Performance analysis has been used to understand game tactics (Peña & Navarro, 2015), inform recruiting decisions (Stewart et al., 2007) and quantify performance (Duch, Waitzman, & Amaral, 2010). Performance analysis has been posited to gain further competitive advantage when paired with a theoretical framework (Balagué et al., 2017; Couceiro et al., 2016; Gerrard, 2016; Glazier, 2017). Ecological dynamics can provide an alternate lens by which performance analysis can explore sport. An ecological viewpoint emphasises the importance of the interaction between the individual, environment and task constraints. Understanding this interaction in competition settings may aid the design of training environments which are representative. An RLD can be created through the implementation of a CLA to manipulate constraints to mimic the competition environment. Determining the influence of constraints is complex. Traditional analysis techniques and methodologies in team sports are able to adequately analyse a complex interacting systems (Ribeiro et al., 2019). Thus, the application of non-linear and multivariate approaches could be applied to address this limitation. Machine learning offers a range of techniques which can help utilise data and incorporate an underlying theoretical framework symbiotically to enhance performance analysis. However, these techniques can provide complex outputs which are not readily interpretable or able to be implemented in the applied setting. Visualisations provide an opportunity to aid the enhancement of performance analysis by making machine learning outputs more accessible. Therefore, performance analysis methodologies could be furthered by the combination of ecological dynamics and machine learning.

CHAPTER THREE - STUDY I

Methodological considerations for the promotion of interdisciplinarity in sport science

Chapter Overview

Chapter Three is the first of the four studies contained in this thesis. The study applied an ecological dynamics rationale to sport science with the aim to aid the implementation of an interdisciplinary approach to sports performance research. Developments in fields such as technology, analytics and the perceptual sciences can accelerate the benefits of interdisciplinary approach to many of sport's most pervasive performance questions and challenges.

This chapter contains a declaration of co-authorship and co-contribution (Section 3.1), an abstract (Section 3.2), introduction (Section 3.3), subsections on technology (Section 3.3.1), analytics (Section 3.3.2) and perceptual science (Section 3.3.3). This chapter finishes with a concluding remarks (Section 3.4) section.

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3.1 Declaration of co-authorship and co-contribution

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

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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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.

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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;

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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

5. The original data will be held for at least five years from the date indicated below and is stored at the following **location**(s):

All electronic data will be stored on the Victoria University R Drive. This is a secure central storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Alice Sweeting	5	Assisted with methodology design, feedback and revisions	[redacted]	8/10/20
Carl Woods	5	Assisted with positioning theoretical framework, feedback and methodology		8/10/20
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.		8/10/2020

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3.2 Abstract

Commonly classified as individual, task or environmental, constraints are boundaries which shape the emergence of functional movement solutions. In applied sport, an ongoing challenge is to improve the measurement, analysis and understanding of constraints to key stakeholders. Methodological considerations for furthering these pursuits should be centred around an interdisciplinary approach. This integration of methodology and knowledge from different disciplines also encourages the sharing of encompassing principles, concepts, methods and data to generate new solutions to existing problems. This narrative review discusses how a number of rapidly developing fields are positioned to help guide, support and progress an understanding of sport through constraints. It specifically focuses on examples from the fields of technology, analytics and perceptual science. It discusses how technology is generating large quantities of data which can improve our understanding of how constraints shape the movement solutions of performers in training and competition environments. Analytics can facilitate new insights from large and complex data through enhanced non-linear and multivariate analysis techniques. The role of the perceptual sciences is discussed with respect to generating outputs from analytics that are more interpretable for the end-user. Together, these three fields of technology, analytics and perceptual science may enable a more comprehensive understanding of constraints in sports performance.

3.3 Introduction

Sport science, in general, has long been criticised for its insular nature, with various sub-disciplines typically looking to solve existing problems internally (Balagué et al., 2017; Buekers et al., 2017; Burwitz et al., 1994; Davids et al., 1994; Elliott, 1999). In research, this has manifested in the establishment and reproduction of sub-discipline specific methodologies (Cardinale, 2017; Glazier, 2017). In practice, this is often observed in the separation of departments (e.g. strength and conditioning, medical and performance analysis) in high-level sporting organisations, culmzinating in isolated and siloed thinking (Otte et al., 2020; Rothwell et al., 2020). These issues may be due to a variety of reasons, such as disciplines researching sport at varying levels from molecular to the environment, whilst also applying discipline specific terminology (Balagué et al., 2017; Glazier, 2017). Within the tertiary education sector, the fast growth of sport science has lead to a focus on specialisation (Hristovski et al., 2017; Hristovski et al., 2014), which has partially been attributed to lack of an overarching, unifying framework (Glazier, 2017; Hristovski et al., 2017). Furthermore, current practices are often seen to offer the illusion of integration, however, do not fully combine methods and techniques alongside theories and concepts (Balagué et al., 2017).

Accordingly, there have been numerous calls for sport science to progress beyond this insularity and embrace an inter- and even transdisciplinary approach (Buekers et al., 2017; Burwitz et al., 1994; Button & Croft, 2017; Glazier, 2017; W. H. Newell, 2001; Piggott et al., 2019; Woods, Robertson, Rudd, Araújo, & Davids, 2020). Adoption of an interdisciplinary approach in sport, whilst challenging, could serve to: i) coordinate and unify activity, ii) communicate translatable ideas coherently, and iii) design and quantify activities which support the emergence of complex and adaptive behaviours (Balagué et al., 2017; Glazier, 2017; Piggott et al., 2019; Rothwell et al., 2020). For instance, if practitioners could operate more collaboratively, it could improve the allocation of time and resources by limiting the duplication of data collection and analysis. Data and its subsequent analysis could also be better communicated through consistent language which may aid the transfer of concepts and ideas between disciplines (Rothwell et al., 2020). Through this, an enhanced ability to address some of sport's most pervasive performance questions and challenges could be gained.

A true interdisciplinary approach would see sports performance disciplines working collaboratively to fully encompass principles, concepts, data and methods to solve problems and support practice (Glazier, 2017). This could result in enhancements of learning, which could then be shared between a range of operational areas, like talent identification, talent selection, performance analysis and coaching (Freedson, 2009; Piggott et al., 2019). Independent methodologies and measurement techniques could be reconciled to build upon and learn from one another. Interdisciplinarity offers collaborative problem-solving which may potentially lead to enhanced inquisition, the identification of new questions and the resolving of existing problems (Hristovski et al., 2014). For interdisciplinarity to occur, new methods and procedures are required, which may challenge engrained and culturally pervasive disciplinary norms.

Frameworks such as ecological dynamics or Newell's constraint model offer a basis upon which sports performance can be measured (Glazier, 2017; K. M. Newell, 1986). Either has the ability to act as a vehicle upon which an interdisciplinary approach could be implemented (Araújo et al., 2006), and may aid the alignment of methods and data (Glazier, 2017). Ecological dynamics is the integration of concepts from ecological psychology (Gibson, 1979), complexity sciences (Seifert et al., 2017), and coordination dynamics (K. M. Newell, 1986; Seifert & Davids, 2017). Newell's constraint model (K. M. Newell, 1986) and its application views skill, learning, development and expertise as emergent properties of a functionally adaptable and evolving relationship formed between an individual and the constraints of their environment (A. M. Williams & Hodges, 2004). It is noteworthy that these rationales are not localised to a single sport science discipline, rather they seek to enhance the understanding of related to concepts such as skill, performance, learning and expertise (Button, Seifert, Chow, Davids, & Araújo, 2020).

Constraints are understood as the boundaries which shape the emergence of functional movement solutions (Davids et al., 2008), and are commonly classified into individual, task and environmental categories (K. M. Newell, 1986). Individual constraints can be defined as structural (e.g. body dimensions, technical attributes), historical (e.g. development of resilience, experience) and/or functional (e.g. motivation, cognition) (Davids et al., 2013; Davids et al., 2008; Immonen et al., 2018). Task constraints are typically defined as rules (e.g. laws of the game, boundary markings), task goals, and/or instructional features (e.g. coach instruction or umpire feedback) (Cordovil et al., 2009; Greenwood et al., 2016; Immonen et al., 2018; Orth et al., 2014). Environmental constraints can be physical (e.g. weather, light, gravity) or sociocultural (e.g. values, cultural beliefs, peer support) (Davids et al., 2013; Davids et al., 2008; Mooney et al., 2016). It has been proposed that task constraints are emergent properties of a system which are able to be distributed between the individual and environment (Balagué et al., 2019). Moreover, constraints have been hypothesised to interact and be correlated via circular causality and can be nested based on characteristics time-scales (Balagué et al., 2019).

An understanding of the manipulation of constraints and their impact on skilled performance is, therefore, central to the design of activities intended to promote performance and learning in sport. This can be achieved through the manipulation of constraints to design representative practice tasks which preserve key information-movement couplings experienced during competition. However, a central feature of constraints and their impact on emergent movement solutions relates to their interaction (Button et al., 2020; Davids et al., 2008). The interaction between constraints is often misunderstood in both practice and research given previous methodological limitations relating to their measurement and interpretation (Glazier, 2017). A methodological limitation is the collection of discrete events without accounting for constraints or the context influencing these events (Robertson et al., 2019). For example, how do constraints such as time in possession, pressure type, playing at home or away, and/or fatigue state interact to influence the emergence of skilled actions in team sports (Robertson et al., 2019)? Future research could overcome this through the use of technology to capture constraints like these, and then applying a multivariate analysis technique, could help practitioners understand their influence on emergent behaviour.

Fortunately, for multiple reasons, an interdisciplinary approach to measuring constraints in applied sport is arguably more feasible now than ever before. Recent improvements to a number of seemingly disparate fields and disciplines has the potential to progress this opportunity. Using examples from technology, analytics and the perceptual sciences, this review details how advancements in a range of fields can be leveraged to achieve interdisciplinarity and disciplinary integration in high performance sport.

3.3.1 Technology

Ongoing, and recently accelerated, improvements to the field of technology have enhanced the measurement of almost all aspects of sport (Miah, 2017). Sport science disciplines, including coaching and performance analysis have traditionally used largely manual methods to measure constraints in practice and competition. However, technology has made it possible to capture these constraints more efficiently and accurately as well as in a more detailed manner (Glazier, 2017). These improvements have impacted a range of disciplines, leading to the manufacturing of better-quality hardware, increased feasibility of athlete tracking and enabling the automated capture of events through computer vision. For instance, developments such as video annotation software enabled practitioners to move from pencil, paper and stopwatch techniques to facilitating the recording of match events and corresponding contextual information in greater detail (O'Donoghue, 2009). More recent technological developments have enabled the capture of an athlete's location on a playing field through global and local positioning systems as well as optical technologies (Gudmundsson & Horton, 2017; Gudmundsson & Wolle, 2014). Presently, such systems are now capable of providing semi- or automated detection of athlete actions (Le et al., 2017; Nibali, He, Morgan, & Greenwood, 2017).

In addition to incremental improvements, some technological developments have facilitated the identification and measurement of variables and metrics which were previously unrecognised in research and practice. For example, eye-tracking, the detection of emotion in competition (Joshi, Tripathi, Soni, Bhattacharyya, & Carman, 2016; J. T.-y. Wang, 2011), and automatic marker-tracking systems (Gudmundsson & Horton, 2017; Le et al., 2017) have offered insight into the non-linear and complex interaction between variables in near real-time – clarity which is not possible with the human eye alone (Corbett et al., 2017; S. Morgan, 2011). Consequently, the number of individual constraints which can be recorded has continued to grow with the development and implementation of technology. A selection of these constraints are reported in Table 1. As technology continues to develop, so too will the opportunities to improve the quality of constraint measurements. Further opportunities exist to develop these technologies with knowledge from other disciplines such as agriculture, city planning and the military (Table 1). However, as observations are embedded in context, the measurement and collection of reliable constraint data is required to take place without losing the validity required for scientific rigour and thereby aid in promoting experimental representative design (Newcombe, Roberts, Renshaw, & Davids, 2019).

Table 3.1. A selection of constraints and contextual factors from team sports unless otherwise specified, which can currently be measured, or could be better measured through improvements in technology

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Events	Task	Location and type of match event	Kempton et al. (2016) O'Shaughnessy (2006)	Automated ball tracking through computer vision	
	Task	Sport Specific Events e.g., Australian Football - Kick type (drop punt, snap, etc.,) Hockey - hit type	Slade (2015) Hughes and Franks (2004)	Automated detection of events via computer vision or device (e.g., IMU) on athlete / equipment (i.e., ball or stick)	Traffic event detection (Al Dhanhani, Damiani, Mizouni, & Wang, 2019)
	Task	Shot location - Angle/Distance of goal face visible	Pocock et al. (2018) Goldsberry (2012)	Player and ball tracking aligned with game logs	
	Task	Time in possession - Individual possession length - Length of possession chain - Team split of previous 10 mins	Higham et al. (2014) Robertson et al. (2019)	Player and ball tracking aligned with game logs	

Table 3.1. cont.

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Events cont.	Task / Individual	Shot trends: 'hot hand fallacy" - team - individual	Skinner (2012) Bar-Eli et al. (2006)	Player and ball tracking aligned with game logs	
	Individual	Disposal efficiency - in game - history	Pocock et al. (2018) Reich et al. (2006)	Player and ball tracking aligned with game logs paired with analytics	
	Task	Available Space - Physical pressure - # players between ball & goal - Ratio of attackers to defenders	Rein, Raabe, and Memmert (2017) Alexander et al. (2019)	Player and ball tracking paired with improved analytics Proximity sensor	Emotional response in crowds (Engelniederhammer, Papastefanou, & Xiang, 2019)
	Task	Kick distance	Blair, Roberston, et al. (2018) Blair, Duthie, Robertson, Hopkins, and Ball (2018)	Ball tracking Automated measurement through computer vision	Automated detection of distances in cars (Emani, Soman, Variyar, & Adarsh, 2019)

Table 3.1. cont.

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Events cont.	Individual / Task	Physical output - game time played - time between efforts - High speed metres	Almonroeder et al. (2018) Sarmento et al. (2018)	Player and ball tracking paired with match events	
	Task	Ball weight	Nimmins et al. (2019) Fitzpatrick et al. (2018)	Computer vision	Computer vision to estimate weight of livestock (Nugraha & Wahyu, 2018)
Individual	Task	Coaching - technique / feedback - game style - enable self-regulation	Wulf and Lewthwaite (2016) Wrisberg (2007)	Recording and natural language processing Speech to text software	Military detection of keywords (Gundogdu & Saraclar, 2019)
	Individual	Dominate Side e.g., preferred foot	Cust, Ball, Sweeting, and Robertson (2019) Ball (2011)	Automated detection through computer vision	

Table 3.1. cont.

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Individual cont.	Individual	Heart Function (Heart Rate, Oxygen saturation)	Klusemann et al. (2012) Dong (2016)	Sensors in uniforms	Sensors built into clothing (Zhang, Yu, & Zhong, 2019)
	Individual	Mental Components: e.g., fatigue, brain activity, motivation, resilience, confidence, decision-making skill, emotion	Russell et al. (2019) Joshi et al. (2016)	Portable brain electrical activity machines	Health sector development of portable EEG (Chuang & Lin, 2019)
	Individual	Player characteristics: i.e., physical, experience, playing position	Piette et al. (2010) Sarmento et al. (2018)		
	Environment	Social - Cultural - Interactions	Anshel, Sutarso, and Jubenville (2009) Davids et al. (2006)	Proximity sensors	Social proximity using Bluetooth (Garcia-Alonso et al., 2020)
	Individual	Recovery (training load)	Halson (2014) Gastin, Fahrner, Meyer, Robinson, and Cook (2013)	Ubiquitous monitoring through 24/7 sensors	Health sector monitoring at risk patients (Li, Ma, Chan, & Man, 2019)

Table 3.1. cont.

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Context	Individual	Sleep	Juliff, Halson, and Peiffer (2015) Halson and Juliff (2017)	Improvements in sleep tracking technology	Validation of non-invasive sleep technology (Toften, Pallesen, Hrozanova, Moen, & Grønli, 2020)
	Task	Difference in team quality	Robertson and Joyce (2018) A. Franks et al. (2015a)		
	Task	Defensive style / intent	Tan et al. (2017) J. Wang et al. (2018)	Player and ball tracking aligned with match log	
	Environment	Opposition characteristics i.e., physical characteristics, experience, playing position	A. Franks et al. (2015a) Milanese, Piscitelli, Lampis, and Zancanaro (2011)		
	Task	Scoreboard - margin /scoring trends	Goldman and Rao (2012) Pocock et al. (2018)	Automation through computation	
	Environment	Time in season Fixture Type	Dellal et al. (2011) Soroka and Lago-Peñas (2016)		

Table 3.1. cont.

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Context cont.	Environment	Playing Surface: - Material i.e., grass (hard, soft, wet, dry) - Dimensions	Bartlett, James, Ford, and Jennings-Temple (2009) Crowther et al. (2019)	Racetrack Penetrometer Clegg-Hammer Magnetic Layer Detection	Magnetic layer detection to measure top soil density (L. Liu et al., 2019)
	Task	Pitch dimensions i.e., (area, depth of pockets)	Klusemann et al. (2012) Kelly and Drust (2009)		
	Environment	Venue - crowd, stadium type (roof, open), distance travelled, noise	José Gama et al. (2016) Goldman and Rao (2012)	Computer vision to monitor crowd emotion	Emotion tracking for city planning (Ashkezari-Toussi, Kamel, & Sadoghi-Yazdi, 2019)
	Environment	Weather (rainfall, wind, sun position)	Thornes (1977) Ely, Cheuvront, Roberts, and Montain (2007)	Wireless sensor network	Weather impact on air traffic management (Reitmann, Alam, & Schultz, 2019)
	Task	Time: Elapsed/remaining in - Period - Game	Pettigrew (2015) Sandholtz and Bornn (2018)	Automation through computational timing	

Table 3.1. **cont.**

Group	Constraint Category	Constraint / Context	Constraint examples in the literature	How technology can improve measurement of this constraint	Technology applications in other disciplines
Match Context cont.	Task	Time elapsed since last: - Foul - Stoppage - Turnover - Score	Andrienko et al. (2017) Skinner (2012)	Automation through computational timing	
	Task	Team synergy	Araújo and Davids (2016) Araújo, Ramos, and Lopes (2016)	Ball and player tracking aligned with match log Facial expression extraction	Emotion tracking for city planning (Ashkezari-Toussi et al., 2019)

To represent the influence of technology on the measurement of constraints, the concept of pressure in a team sport context presents a useful example. As a scientific construct, pressure has been measured in multiple ways; through the proximity of opponents on the field as measured by player tracking systems (Andrienko et al., 2017; Clemente, Martins, Couceiro, et al., 2016), an athlete's physiological and emotional response measured via sensors (Engelniederhammer et al., 2019; Joshi et al., 2016), or through the context of a game via the scoreboard or time remaining (Goldman & Rao, 2012; Pocock et al., 2018). Adding more data types to define pressure more comprehensively will likely lead to a greater understanding of its influence on performance outcomes.

Extending these ideas, technology can enable greater clarity with regards to the measurement of constraints players experience during competition. Beyond helping practitioners contextualise actions observed during competition, it can assist with the design of practice tasks that are more representative of the requirements of competition to support athlete development and learning (Ireland et al., 2019). For example, by understanding the key constraints that shape athlete behaviour, practitioners could design them into practice tasks, thereby preserving information-movement couplings to support athletes in becoming more self-regulating in performance (Ireland et al., 2019).

Of course, both researchers and practitioners will always experience some limitations with respect to the volume of data they collect. Furthermore, the continual addition of new types of data has the potential to overcomplicate modelling and limit user interpretability (Davids & Araújo, 2010). From a resourcing perspective, it may not be feasible to collect all possible data sources in training or competition environments. In some cases, the feasibility of measurement may be influenced by the sport itself. For example, whilst an inertial movement unit could provide insight into constraints and contextual factors surrounding limb motion, most governing sports organisations restrict the use of such devices during competition (Ghazikhanian & Cottrell, 2018). Additionally, ball tracking systems in team sports are becoming more commonplace in practice, yet the resources to analyse and interpret the outputs remains intensive (S. Liu et al., 2017; McGarry, 2009). Thus, finding a feasible 'sweet spot' for the collection of data is required in practice to enable the most impactful implementation of technology.

3.3.2 Analytics

One criticism leveraged at ecological dynamics points towards its complexity, with research to date being largely conceptual or performed in a laboratory (Farrow & Robertson, 2017). The measurement of constraints in practice have often been reductionist in approach (Newcombe et al., 2019), emphasising either one or two constraints that are measured in isolation (Robertson et al., 2019). This can provide rigor in relation to the methodological approach, however it is less representative of the environment being explored (Newcombe et al., 2019). This may result in an overly narrow and potentially even misleading interpretation of sports performance by not accounting for, or misrepresenting, the nuances of a complex system (Couceiro et al., 2016; Glazier, 2010; McLean et al., 2019). Thus, whilst the literature referred to in Table 1 is encouraging with respect to the large volume of constraints captured in performance settings, it is important to recognise that i) constraints do not act or interact independently and ii) not everything can be measured and analysed in research or practice.

Analytics refers to the methods based on the computation of statistics and data (Analytics, 2020) and, therefore, considers both computation and algorithms. Machine learning, the application of artificial intelligence that affords a system the ability to autonomously learn through experience or example data, has had increased application in sport (Alpaydin, 2010). Analytics may aid sport science practices in identifying complex and non-linear patterns within datasets. Machine learning techniques have been used in sport to quantify defensive patterns (Le et al., 2017), as well as predict events (Cervone et al., 2014; Pocock et al., 2018) and match outcomes (Cervone et al., 2014; Deshpande & Thakare, 2010). Improved analytical methodologies allow for more complex phenomena, such as the interaction of players, to be measured (Benito Santos et al., 2018; Gudmundsson & Horton, 2017). Accordingly, analytical approaches applied are an important aspect of performance research and decision-making (Robertson, Back, et al., 2016; Schelling & Robertson, 2020; Sicilia et al., 2019), supporting the experiential knowledge of professional practitioners. To make analytics applicable to industry settings, practitioners may need enhanced skillsets to use data tools which can analyse and summaries big datasets, and/or seek to establish bespoke workbooks that automate preferred data visualisations following capture. In the time-constrained environment of high-performance sport, analytics may streamline decision-making across multiple departmental areas (Benito Santos et al., 2018; Gudmundsson & Horton, 2017; James et al., 2013).

A key benefit of analytics when applied to sports performance, relates to its flexibility. Specifically, in regards to how different machine learning algorithms can often be used interchangeably on the same dataset (Duro, Franklin, & Dubé, 2012; Fahey-Gilmour et al., 2019; N. Williams, Zander, & Armitage, 2006). This can enable a problem to be viewed through multiple lenses which may be implemented or visualised differently based on user preferences. Returning to the abovementioned example, it has been acknowledged that pressure has been analysed in various ways. For example, weighted densities paired with linear and quadratic functions have been used to understand defensive players movements through spatiotemporal data in soccer (Andrienko et al., 2017), whereas in basketball, matrix factorisation and regression models have been utilised for the same purpose (A. Franks et al., 2015a). The creation and measurement of a pressure metric can be achieved with either discrete or continuous variables. Representation of pressure in a categorical format (i.e., 'high' or 'low') may make for easier stakeholder comprehension and implementation in the applied setting. Irrespective of the format in which the data is represented, however, more context than solely player movement is required to fully measure pressure. Thus, using player density or pitch control (Fernández & Bornn, 2018; Spencer, Morgan, Zeleznikow, & Robertson, 2017a), alongside score board margin, time remaining and individual traits of an athlete could offer greater insight into the pressure experienced at any given time.

The collection of more data related to different interacting constraints can ultimately make the analysis of variables more difficult. The principle of parsimony is critical within analytics to strike a balance between feasibility and obtaining a high-level understanding of a phenomena of interest. Without enhanced analytical tools, the translation of model outputs which contain a large number of variables into meaningful information remains a challenge (Davids & Araújo, 2010; Rhee & Rao, 2008). Parsimony relates to achieving a balance between collecting enough variables to sufficiently support an evaluation but not so many that only provide small improvements to the understanding (Robertson, 2019; Robertson & Joyce, 2019). Within sport, parsimony is vital to the uptake of new models and decision support systems, as it can reduce data redundancies and optimise time investments. For example, if a model requires five variables to achieve 80% accuracy on a given problem, the time and resources required to collect an additional ten variables to improve accuracy by 5%, may not outweigh the benefit of a slightly less accurate model. This has useful applications in scenarios whereby a model requires implementation across multiple environments. For instance, comparing junior athlete performance with professional competition for team sport scouting purposes may see the user having access to differing levels of data, leading to a lack of direct comparability of performances. Many variables used within the professional competition may not be available at lower levels; thus, invoking the notion of parsimony forces the user to focus on including those variables that are not only the most important, but also readily available across all levels of competition.

Parsimony also helps to avoid problems with overfitting. Overfitting describes a model, which is generated specifically to a training dataset, but where the results are not generalisable or validated on a new or unseen test dataset (S. Morgan et al., 2013; Robertson, Back, et al., 2016). In the example above, a scouting model used in professional competition may show accurate predictive performance when applied to professional players, but due to its large number of inputs (amongst other factors) may generalise less well to other competition levels (Schelling & Robertson, 2020). Striking a compromise between parsimony and model accuracy is a complicated exercise, particularly in the field, but is an increasingly important consideration as sports performance models become more complex and detailed.

3.3.3 Perceptual science

The growth in data along with the enhanced analysis of this data has been emphasised to this point of the review. However, without the output from such analyses being appropriately communicated to and interpreted by key stakeholders, the gains achieved by sport science will go unrealised. Learnings from the perceptual sciences could hold the key to assist in this area. Perceptual sciences refers broadly to the integration of neuroscience, computer science and psychology with the aim to understand the link between external properties and cognition (Goldstone, 1998; Green, 1998). Specifically, components of cognitive science such as psychophysics, alongside the art of visualisations, may be used to enrich the interpretation of analytics and explain why some visualisations better enable the detection of key information. Together, the concepts of cognitive science and the perceptual sciences can provide a foundation and guide for the utilisation of the science and language of visualisations to maximise comprehension and improve the communication of complex phenomena in sport. In doing so, visualisations may enable the user to identify the relationship between an individual and their environment with enhanced clarity by preserving the complex and non-linear interactions at work, which are typically reduced through traditional, linear approaches .

Visualisations have been proposed as a method to leverage data communication to highlight findings clearly with precision and efficiency. This is required as despite the improvements in technology and analytics, a linear improvement in performance has not occurred (Couceiro et al., 2016). This may be partially due to a user's reduced ability to gain insight from numerical data, as tables may be inferior to visualisations in communicating results (Spence & Lewandowsky, 1991). Visualisations provide a tool to translate numbers into a simpler medium for ease of interpretation and implementation (Green, 1998). This may be due to the increased cognitive load required to comprehend numeric compared with visualisations (Green, 1998; Kale et al., 2018). Thus, as analytical model outputs become more complex, visualisations can help to support the user's comprehension. Ultimately, if such output is not interpretable or operationalisable, even the best performing model will not be implemented by key stakeholders in the applied setting (S. Liu et al., 2017; Robertson, 2019).

Given the inherent complexity of ecological dynamics, visualisations are critical in their ability to indirectly convey key information. Visualisations are an essential tool to enable the appreciation of complex and multidimensional constraints in a system. The ability to visualise multiple variables may further enhance the communication of complex information. For instance, five dimensions can be displayed and manipulated through the two regular axes as well as hue, shape and size of data points. The impact of visualisations on stakeholder decision making has been examined in forecasting, communication and planning (Fagerlin et al., 2011; Fernandes et al., 2018; Padilla, Creem-Regehr, et al., 2019; Padilla et al., 2017). Furthermore, visualisation aesthetics have been linked with an individual's engagement, enjoyment and memorability (Cawthon & Moere, 2007; Fagerlin et al., 2005; Hullman, Qiao, Correll, Kale, & Kay, 2018; Pinker, 1990). However, an awareness of inherent biases is also required in the generation of visualisations. Biases are cognitions which prejudice decision making (Arnott, 2006). For instance, as the number of components displayed in a bar chart increases, the accuracy in which the chart is interpreted decreases (Hollands & Spence, 1998). The transition from data and analysis to the creation of a visualisation may aid in the uptake of information and thus, insight in the applied setting (Green, 1998).

Returning to the pressure example discussed in earlier sections, it is apparent that despite its visual potential, pressure or defensive actions are often reported as aggregate data, for example as a frequency count in a table (Griffin et al., 2017; Ireland et al., 2019). However, in scenarios whereby continuous pressure metrics have been proposed (Andrienko et al., 2017; Fernández & Bornn, 2018), visualisations can be used in different ways to provide alternate insights with the same data. For example, Figure 1 provides an example of how Pitch Control can be used to visualise pressure. Pitch control is a concept which defines the probability that an athlete or team has control of a specific point of a certain region of the pitch at a given time point (Fernández & Bornn, 2018). It is based on athlete location, velocity and relative distance from the ball at a given time point, where the aggregate influence of each team's athletes is calculated on a continuous scale to provide a measure of pitch control (Fernández & Bornn, 2018). Specifically, Figure 1a shows an overview of a passer in football (represented by the white dot) at a discrete moment in time during a match. The darker the blue area the more pressure experienced by the passing player, based on their level of 'pitch control'. Such a visualisation can be used to provide further context to the pressure not just surrounding the passer, but the options available to them. Furthermore, the level of pitch control varies throughout a game, which can be visualised as a time series to display how pressure changes for the team in possession throughout a match (Figure 1b). Thus, '1' would represent total pitch control by Team 1, 0.5 represents equal levels of pitch control by both teams and '0' relates to total pitch control by Team 2. Furthermore, visualising pitch control at the location of the passer and receiver may provide insight into game style, risk taking behaviour and decision making (Figure 1c & 1d). For instance, a team may relinquish some pitch control at the location of the passer to create more space at the location of the receiver. This tactic may increase the pressure, or decrease pitch control, at the ball location but lessen the pressure for the receiver. Thus, visualisations may enable the facilitation of the improvements in technology and analytics to be realised. When operationalised in unison, they may help aid decision making and encourage interdisciplinarity – demonstrated by this pressure example, where the use of player tracking data alongside algorithms to generate a pitch control metric and visualisations to help convey this data in a usable format. Thus, appropriate visualisations using the same data or model can improve the communication of findings to key stakeholders and facilitate rapid interpretation and implementation (Kale et al., 2018; Larkin & Simon, 1987; Wilke, 2019).

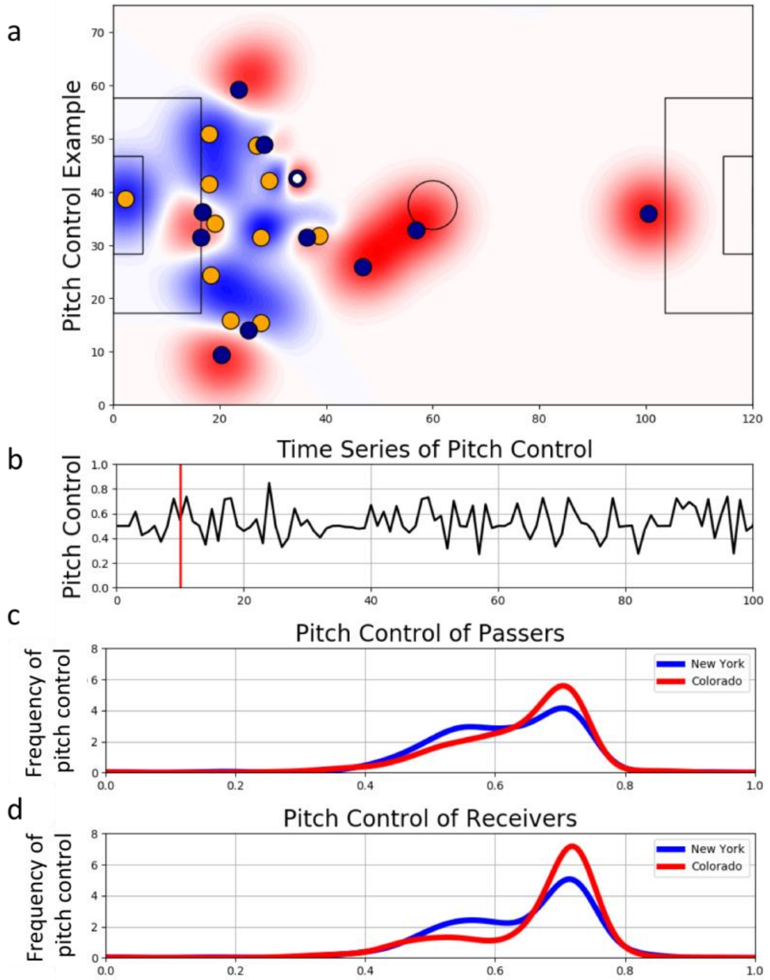

Figure 3.1. **Examples of different ways pressure may be visualised via an exemplar from football. The metric of pitch control is used, a concept which defines the probability that an athlete or team has control of a specific point. a) Static image of pitch with player locations and pitch control at time indicated by red line in 1b. Ball possession is represented by the white circle. b) Time series of pitch control of the attacking team calculated as a minute by minute average of pitch control over course of a game. Where 1 represents total pitch control by Team 1, 0.5 represents equal levels of pitch control of both teams and 0 relates to total pitch control by Team 2. The red line indicates the time Figure 1A was taken from. c) Density plot of the level of pitch control of passer. d) Density plot of the level of pitch control of receiver.**

3.4 Conclusion

This narrative review has provided some methodological considerations for the measurement of constraints though an interdisciplinary approach. The benefits of an interdisciplinary approach could arise from greater consistency between disciplines, more efficient workflows and optimised communication procedures (Rothwell et al., 2020). These improvements may allow for questions to be answered more completely rather than solutions that have origins and applications in a single discipline. This narrative review specifically discussed how the continually developing fields of technology, analytics and perceptual sciences are situated to help guide and support sport science to make the integration between disciplines more feasible. Importantly, these fields are not all encompassing and many others exist which can further the measurement of constraints in applied sport. Whilst other fields may further the development of constraint measurement, interdisciplinarity can also be encouraged through applying an overarching framework (Glazier, 2017). By embracing a true interdisciplinary approach, progress on many of sport science’s most pervasive and important questions can be realised. However, for sport science to continue to progress toward interdisciplinarity, more needs to be done to create environments open to change, where improvements can transcend sub-disciplines. Furthermore, academic institutions need to provide training and education which is supportive of interdisciplinary approaches, as opposed to driving a continued discipline speciality. This may see high-performance sports organisations reassess structures, move away from siloing departments, towards creating integrated, functioning environments where time and resources are available to be utilised in an interactive way. The removal of such barriers may aid sport scientists in adopting the principles of interdisciplinarity.

CHAPTER FOUR - STUDY II

Prevalence of interactions and influence of performance constraints on kick outcomes across Australian Football tiers: Implications for representative practice designs

Chapter Overview

Chapter Four is the second of the four studies contained in this thesis. The study applied concepts from Chapter Three to attempt to understand how constraints interact with one another to influence skilled performance in Australian Football. A comparison was made to understand whether differences existed in the influence of constraints between competition tiers.

This chapter contains a declaration of co-authorship and co-contribution (Section 4.1), an abstract (Section 4.2), introduction (Section 4.3), methods (Section 4.4), results (Section 4.5), discussion (Section 4.6) and conclusion (Section 4.7). The content of this chapter was published in Human Movement Science (Browne, Sweeting, Davids, & Robertson, 2019)

4.1 Declaration of co-authorship and co-contribution

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

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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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.

Peter Ronald Browne — Digitally signed by Peter Ronald Browne Date: 2020.10.10 11:48:47 +11'00'	10/10/2020
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;

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3. There are no other authors of the publication according to these criteria;
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5. The original data will be held for at least five years from the date indicated below and is stored at the following **location**(s):

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Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Alice Sweeting	5	Assisted with methodology design, feedback and revisions	[redacted]	8/10/20
Keith Davids	5	Assisted with positioning theoretical framework, feedback and methodology		9/10/2020
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.		8/10/2020

Updated: September 2019

4.2 Abstract

Representative learning design is a key feature of the theory of ecological dynamics, conceptualising how task constraints can be manipulated in training designs to help athletes self-regulate during their interactions with information-rich performance environments. Implementation of analytical methodologies can support representative designs of practice environments by practitioners recording how interacting constraints influence events, that emerge under performance conditions. To determine key task constraints on kicking skill performance, the extent to which interactions of constraints differ in prevalence and influence on kicking skills was investigated across competition tiers in Australian Football (AF). A data sample of kicks (n = 29,153) was collected during junior, state-level and national league matches. Key task constraints were recorded for each kick, with performance outcome recorded as effective or ineffective. Rules were based on frequency and strength of associations between constraints and kick outcomes, generated using the Apriori algorithm. Univariate analysis revealed that low kicking effectiveness was associated with physical pressure (37%), whereas high efficiency emerged when kicking to an open target (70%). Between-competition comparisons showed differences in constraint interactions through seven unique rules and differences in confidence levels in shared rules. Results showed how understanding of key constraints interactions, and prevalence during competitive performance, can be used to inform representative learning designs in athlete training programmes. Findings can be used to specify how the competitive performance environment differs between competition tiers, supporting the specification of information in training designs, representative of different performance levels.

4.3 Introduction

Representative learning design (RLD) is a key concept in the theoretical framework of ecological dynamics that advocates the manipulation of task constraints in training. This approach to training and practice in sport can shape continuous individual-environmental interactions to facilitate the emergence of functional (relevant) decision-making and actions of athletes under competitive performance conditions in sport (Davids et al., 2008; McCosker et al., 2019; Pinder et al., 2011). Implementing RLD in training seeks to provide faithful practice simulations of competitive environments to enhance performance (Pinder et al., 2011). When preparing athletes for performance, the implementation of representative training designs requires a detailed, evidence-based understanding of how key task constraints interact to influence behaviours (Renshaw, Davids, Newcombe, & Roberts, 2019). The level of task design fidelity can be informed through recorded data on the prevalence and interaction of constraints in a competitive performance environment (Davids et al., 2006; Robertson et al., 2019). It has been argued that analysis and comprehension of the nature of constraints in performance settings is a key role for coaches in practice design (Araújo, Davids, Bennett, Button, & Chapman, 2004).

Currently, events and outcomes are captured in statistical analysis of team sports performance. This typically occurs through player trajectory analysis and frequency count data recording performance variables including kicks, tackles and fouls, without accounting for the context in which they emerge (Gudmundsson & Horton, 2017). Determining the influential constraints within competitive performance, with respect to their impact on key performance outcomes, would provide an evidence-based approach to practice designs, harnessing the power of performance analysis and evaluations (Farrow & Robertson, 2017; Robertson et al., 2019). When constraints are used for this purpose, they tend to be viewed in a univariate manner, with respect to match context. For example, score margin and kick location (Pocock et al., 2018; Reich et al., 2006), playing at home or away (Goldman & Rao, 2012), or dynamic game conditions (Farrow & Reid, 2010) are used to discern various aspects of performance. However, it has been proposed that multiple constraints *interact* to influence (a) team sports performer(s) concomitantly during skilled activities (Araújo & Davids, 2018). Thus, a constraints-led perspective on performance analysis can facilitate the creation of a more effective and efficient representative design in practice. This is due to highlighting the importance of the greater team sports performance system and how it is a combination of interacting sub-systems (Davids et al., 2006). By evaluating a performance outcome with respect to interacting constraints, the context surrounding competitive performance can be considered, providing an objective, evidence-based assessment of performance.

A recent study illustrated a methodology to identify the most commonly occurring constraint interactions experienced in field kicking in the AFL, through utilising a machine learning algorithm (Robertson et al., 2019). The higher the number of constraints in a model, the greater the associated level of understanding of performance outcomes (Araújo & Davids, 2016; Davids & Araújo, 2010; Davids et al., 2006; Robertson et al., 2019). However, the feasibility of including all constraints and contextual variables in a performance analysis model is often low in an applied practice setting, given the exponential number of interactions which may exist between key performance variables (Robertson et al., 2019). The application of machine learning may identify *meaningful interactions of constraints* in competition which may then be reproduced in representative designs of practice. Critically, this process is not feasible through human observation or the application of traditional linear statistical techniques due to limitations of both (Robertson et al., 2019).

Australian Football (AF) is an invasion-style sport played on an oval with 22 players per side, 18 on the field and 4 on the interchange (Gray & Jenkins, 2010). Due to the large playing area and number of players involved, an understanding of key constraints which shape scoring opportunities is crucial. Kicking is an important action in AF, as it constitutes the predominant form of strategic ball movement and the sole manner in which a goal can be scored. On average, each player executes a kick every ten minutes within an AFL match (R. J. Johnston et al., 2012).

Further, AF is a dynamic sport at all skill levels, with an unpredictable nature due to a large number of varying factors that impinge on performance (Pill, 2014). The completion of a successful kick is a resultant of multiple attributes of the game and the immediate constraints that emerge on the kick, such as opposition pressure, teammates' availability and the current status of the ball carrier (Pill, 2014). Despite this key performance feature, little is known about the interaction of key task constraints placed on these kicks and how these differ across competition tiers. Information on significant performance constraints at different levels of structured competition would facilitate the implementation of task constraints to improve kicking performance in training and games (Farrow, 2010).

Key performance differences have been described between elite, sub-elite and underage athletes across a number of sports. Running distances and high intensity movements differ by age and are greater in elite, compared to high-level female soccer players (Buchheit, Mendez-Villanueva, Simpson, & Bourdon, 2010; Mohr et al., 2008). Within volleyball, performance indicators, physical and physiological outputs differ between elite and sub-elite athletes (D. Smith, Roberts, & Watson, 1992). Yet, no research has been conducted on how constraint interactions can differ on performances between competition tiers. It is possible that constraints interactions may change as a function of competition tier. Whilst the data reported by Robertson et al. (2019) describe constraints interactions within the senior AFL competition, the same manipulations may not provide an RLD in other tiers of AF competition (e.g., junior and club levels). An understanding of the demands of specific competitive performance environments is vital to produce representative designs which align with specific levels of competition.

This study aimed to ascertain where there are differences in the influence and prevalence of constraints which exist between competitive performance at: (i) U18 years of age (U18) competitions, (ii) senior state leagues, and (iii), the professional AF League. Further, it attempts to evaluate how the efficacy of exploring effects of numerous interacting constraints can provide a more inclusive measure of constraint influence on field kicking, compared to uni- and bi-variate approaches.

4.4 Methodology

Data were collected across underage, sub-elite and elite Australian Football competitions from the 2016, 2017 and 2018 seasons (Table 4.1). Approval to conduct the study was obtained by the University Human Research Ethics Committee. A code window was developed in SportsCode (10.3.14, Hudl, Lincoln, Nebraska, United States of America) to record six constraints on field kicking performance, represented as a binary 'effective' or 'ineffective' kick using video footage. A kick was determined to be 'effective' or 'ineffective' based on a range of potentially impinging factors such as kick intent, kick position, number of defenders located near the kicker and kick distance as defined by Champion Data the official statistics provider of the Australian Football League. This was subject to human interpretation. These constraints are shown in Figure 4.1. For example, pressure was coded as a four-level constraint, based on the action and direction of the opposing defender. These were: closing, chasing, physical or no pressure. The constraints categories and levels implemented in this study were based on Champion Data's codes where possible, otherwise they were based upon previous research by Back (2015), Robertson et al. (2019), Ireland et al. (2019), as well as consultations with two experienced coaches from a professional AFL team. A total of 29,153 kicks were coded.

Table 4.1. Breakdown of total kicks per league and tier.

Competition	Tier	Number of kicks
Academy Series	U18 Competition	701
Australian Football League Academy	U18 Competition	170
Australian Football League	AFL	9,005
Australian Underage Championships	U18 Competition	1,890
North East Australian Football League	State league	809
South Australian National Football League	State league	491
South Australian National Football League (Reserves)	State league	657
South Australian National Football League (Under 18)	U18 Competition	998
School Football	U18 Competition	37
TAC Cup	U18 Competition	11,625
Victorian Football League	State league	934
Western Australian Football League	State league	266
Western Australian Football League (Reserves)	State league	28
Western Australian Football League (Under 18)	U18 Competition	1,542
	TOTAL	29,153

Figure 4.1. **Breakdown of categories of constraints and their levels. Each kick is assigned one value from each category. Reprinted from Robertson et al. (2019). Copyright 2019 by Taylor & Francis Ltd, http://tandfonline.com.**

Descriptive statistics (means, standard deviations and 95% confidence intervals, CIs) relating to kick effectiveness were calculated and reported for each individual constraint type. Descriptive statistics relating to kick effectiveness, shaped by pairs of interacting constraint types, time in possession-distance and time in possession-pressure, were obtained.

To determine both the prevalence and influence of constraint interactions on kick outcomes, a rule induction approach was utilised. Rule induction is a branch of machine learning, which is capable of identifying underlying and frequent patterns between variables in a large transactional database (Agrawal & Srikant, 1994; Robertson et al., 2019). Specifically, the '*arules*' package (Hahsler, Buchta, Gruen, & Hornik, 2018) was used to run the Apriori algorithm. The model was set to only produce rules which incorporated five categories of constraint and contained the performance outcome (effective or ineffective) as the resultant. As identified, a benefit of association rules is the ability to find patterns which are typically less identifiable through observation by the human eye (S. Morgan, 2011). A minimum support value of 0.0005 was selected for both models in order to generate a minimum of five rules which met the set criteria.

Data were grouped based on level of competition by U18 (kicks n = 16,963), State level leagues (kicks n = 3,185) and the AFL (kicks n = 9,005), as outlined in Table 4.1. Models were then built for each competition tier using the same criteria outlined above. To compare the rules generated between tiers, the number of unique and duplicated rules were compared alongside their variation in confidence levels (Dudek, 2010).

4.5 Results

The average match kicking effectiveness value, regardless of which constraints were present, was 54%. The overall mean effectiveness values for each level of the six constraints are shown in Figure 4.2. Kicking to an open target resulted in an effective kick 70% of the time, while kicking under physical pressure resulted in the lowest (37%) of kicking effectiveness. Time in possession of 0 to 2 seconds demonstrated a level of 50% effectiveness, whilst time in possession for between 4 to 6 seconds was effective 64% of the time. Possession source, or how the ball was gained, had a clear influence on kick effectiveness with three levels of constraint, ground ball, handball received and stoppage, all representing unstructured and general play, falling below average effectiveness and two types of possession source above average. In contrast, the two constraint levels above average kick effectiveness, sourcing the ball from either a mark or free kick, both represent set plays.

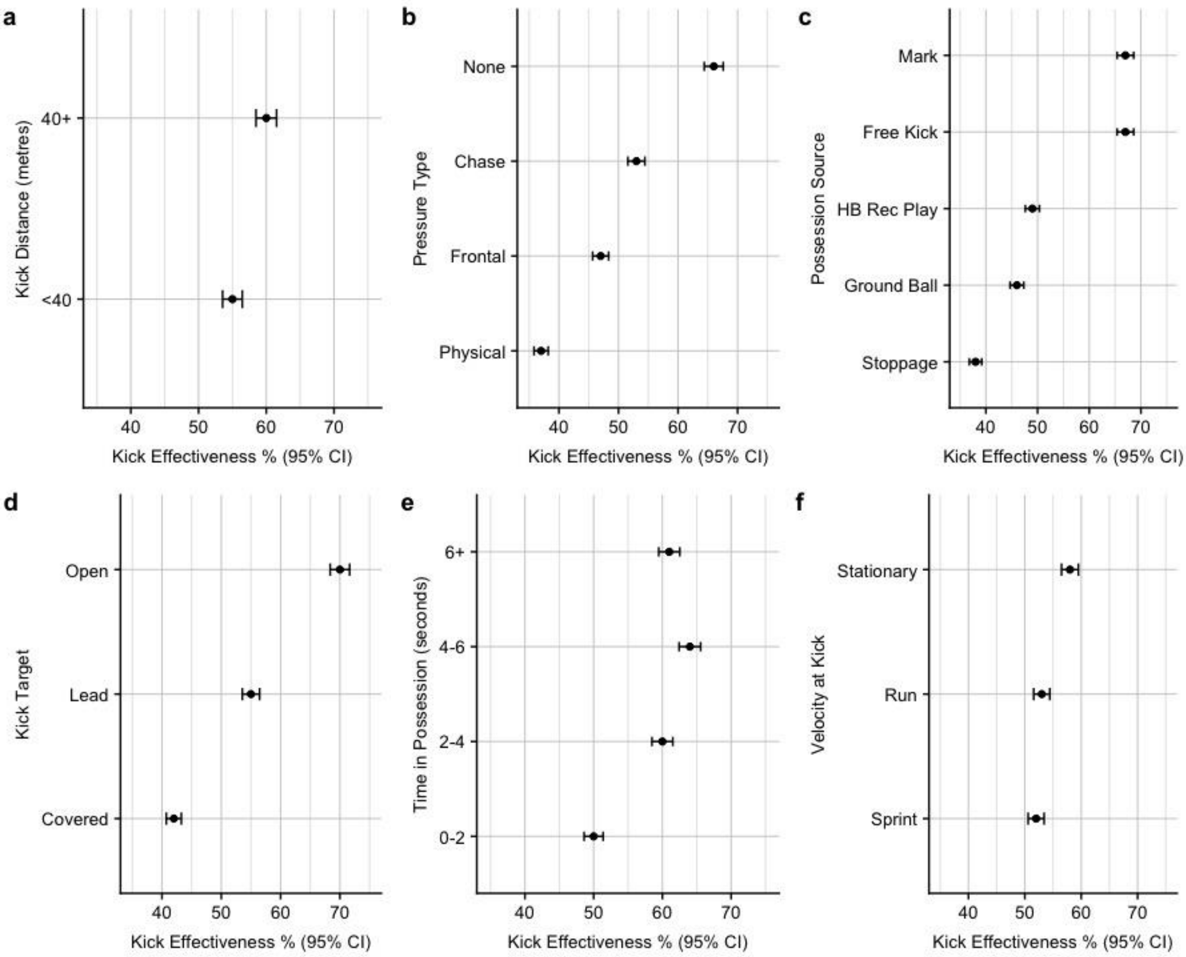

Figure 4.2. **Mean effectiveness (%) and 95% confidence interval (CI) of kicks by constraint type. a) Distance of kicks less than 40 m and greater than 40 m. b) Pressure types of chase, frontal, physical or no pressure. c) Source of possession: stoppage, ground ball, Handball received, free kick or mark. d) Kick target of a covered, leading or open player. e) time in possession measured in seconds, 0 < 2, 2 < 4, 4 < 6 and 6+ seconds. f). Player velocity at kick: sprint, run or stationary.**

As an example of bivariate constraint interaction, how time in possession can interact with pressure is displayed in Figure 4.3. Kick effectiveness is altered by the relationship between pressure and time in possession. A kick under physical pressure from an immediate opponent ranges in effectiveness from 37% to 71%, depending on the level of time afforded to the performer. Under frontal pressure, this varies from 43% to 56%, based on the time in possession. The relationship between kick distance and time also shows a range, with differences between kicks <40 metres long displaying increased effectiveness with longer time in possession: for 4 to 6 secs or > 6 secs. Kicks over 40 metres have increased effectiveness with shorter time in possession: 0 to 2 secs and 2 to 4 secs (Figure 4.3).

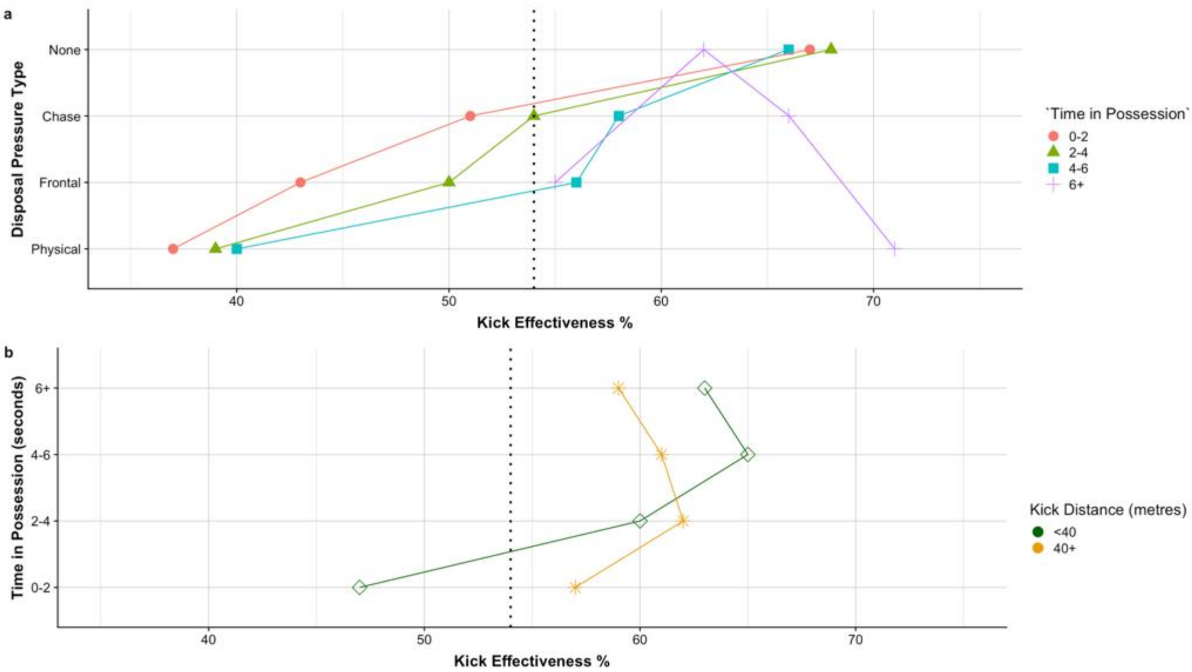

Figure 4.3. Bi-variate example of the interaction of two constraints. Dotted line represents the average kicking effectiveness without taking constraints into account (54%). a) Disposal pressure type by time in possession. b) Time in possession and kick distance.

The rule induction approach resulted in 22 rules, which influenced kick effectiveness, with confidence results ranging from 43% to 87%. Fifteen rules had an influence on kick ineffectiveness, with confidence results ranging from 13% to 85%. Only the top five rules for an effective and ineffective kick were analysed (see Figure 4.4).

Time			Distance		Pressure				Target		Source					Effective kick confidence levels
0-2	2-4	4-6	< 40	40 +	Physical	Frontal	Chase	None	Open	Covered	Free Kick	Stoppage	Ground Ball	HB Received	Mark	
	✓		✓					✓	✓						✓	87.0%
✓			✓					✓	✓					✓		86.9%
		✓	✓					✓	✓						✓	86.6%
✓			✓					✓	✓						✓	84.1%
	✓		✓					✓	✓		✓					83.3%

Time			Distance		Pressure				Target		Source					Effective kick confidence levels
0-2	2-4	4-6	< 40	40 +	Physical	Frontal	Chase	None	Open	Covered	Free Kick	Stoppage	Ground Ball	HB Received	Mark	
✓			✓		✓					✓		✓				14.6%
✓			✓		✓					✓			✓			15.4%
✓			✓			✓				✓				✓		23.3%
✓			✓			✓				✓			✓			23.3%
✓			✓				✓			✓				✓		38.5%

Figure 4.4. Multi-variate analysis results of rules associated with kick outcome. The five rules most strongly associated with effective (green) and ineffective kicks (red) are ranked by the highest and lowest confidence values. Where a tick represents the presence of the performance context within the rule. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

A comparison between U18, state leagues and the national competition athletes was conducted, with the 10 strongest rules based on confidence for each tier outlined in Figure 4.5.

Source	Kick Distance	Target	Pressure	Time in Possession	U18	State Leagues	AFL
					Confidence (%)		
Free Kick	<40	Open	None	0-2	83		
Free Kick	<40	Open	None	2-4	82	82	94
Free Kick	<40	Open	None	4-6	72		
Free Kick	<40	Open	None	6+		82	92
Free Kick	40+	Covered	None	6+		90	84
Ground Ball	<40	Open	None	0-2	72	78	
Ground Ball	<40	Open	Frontal	2-4		72	
HB Rec Play	<40	Open	None	0-2	82	88	94
HB Rec Play	<40	Open	None	2-4	72		
Mark	<40	Open	None	0-2	82	73	100
Mark	<40	Lead	None	0-2			81
Mark	<40	Open	None	2-4	85	83	97
Mark	<40	Covered	None	2-4			77
Mark	<40	Open	None	4-6	83	79	97
Mark	<40	Lead	None	4-6	72	74	
Mark	<40	Open	None	6+			86

Figure 4.5. Rule-based comparison between levels of competition. The top 10 rules based on confidence are displayed and ordered by constraint type. Grey circles indicate that the rule was not present in the top ten rules for that tier.

4.6 Discussion

This study demonstrated how constraint interactions influenced kicking performance, across three performance tiers of AF competitions. Further, the importance of accounting for constraint interaction, as constraints interacted with one another which altered performance outcomes. In research, the interaction of constraints on field kicking has only been examined at the professional tier (Robertson et al., 2019). However, results from the AFL competition only are not representative of other performance tiers. Results demonstrated differences between performance tiers which may enable more specific representative designs in athlete preparation and development, to inform training practices and player evaluation at different performance levels.

Analysis of task constraints in a univariate manner can be misleading, as constraints exist concomitantly and are continually impacting on each other (K. M. Newell, 1986). This study demonstrated the large influence that an individual constraint can have on kick effectiveness. This is illustrated by the considerable difference between the highest and lowest kicking effectiveness between kicking to an open player, who is under no immediate pressure from the opposition (70%) or kicking under physical pressure (37%). The bivariate analysis (see Figure 4.3) demonstrated how the addition of even a single constraint can influence performance outcome to a great extent. Further, Figure 4.3b demonstrates that a constraint such as *time* has a ‘sweet-spot’, meaning that having ball possession for a short or long period of time may not necessarily be advantageous for a performer. Maintaining possession for between 2 to 4 or 4 to 6 secs for kicks under or over 40 metres respectively, may result in the emergence of a higher percentage of effective kicks. However, the addition of further task constraints, which further simulate performance conditions, may offer greater insights into how constraints interactions influence performance.

As identified, the inclusion of additional constraints offers a unique story to the isolated univariate and bivariate approaches. Incorporating conditional constraints interactions in test design could improve the level of task representativeness (Vilar, Araújo, Davids, & Renshaw, 2012). To illustrate the need to account for constraint interaction the ranking of 0 to 2 secs for time in possession will be used. The univariate analysis showed 0 to 2 secs results in an average effectiveness of 50% on kicking performance, only 4% below average. Without the rule induction approach, in which time in possession of 0 to 2 secs is present in the five ineffective kick rules, the potential importance of this constraint may have been overlooked. Figure 4.6 demonstrates how the tallying of additional constraints exhibits that, as more constraint variables are added in performance modelling, a more comprehensive insight into the influence of constraint interactions can be gained. This finding illustrates how comparing an athlete’s performance to average kick effectiveness does not provide a fair comparison on which to judge an individual's performance.

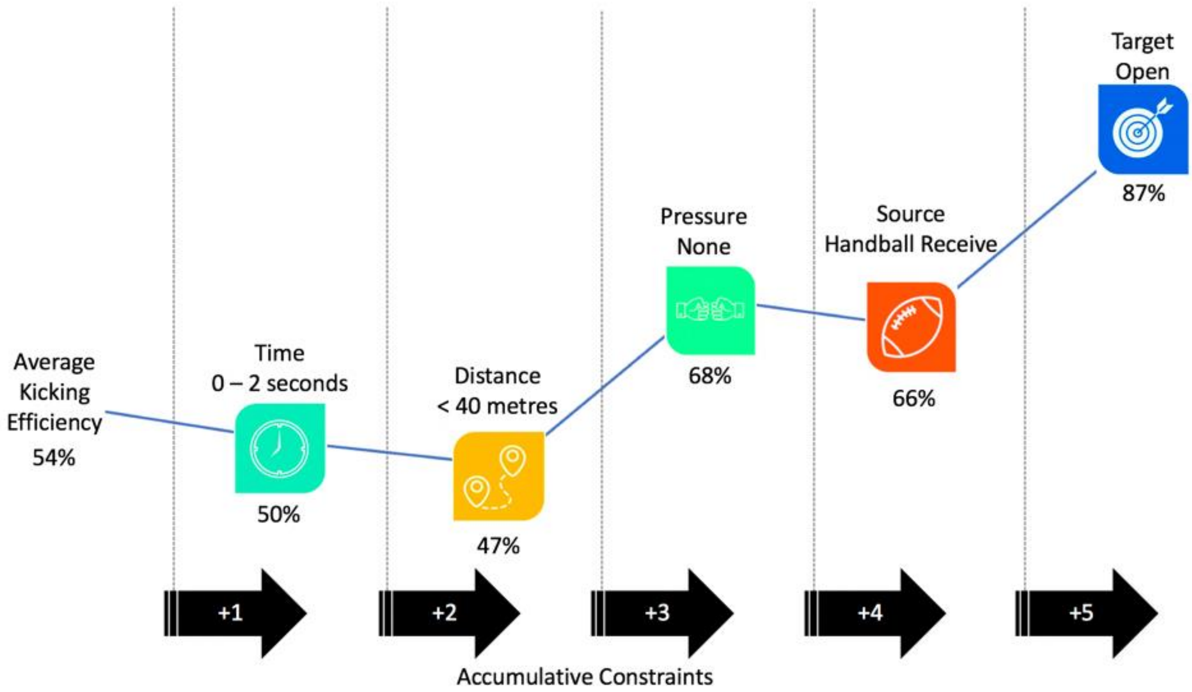

Figure 4.6. **Example of how adding additional constraint variables and considering the constraint interaction alters the mean efficiency of the kick outcome. Percentage values indicate confidence level of an effective kick.**

Understanding the nature of competitive performance constraints could also support an objective consideration of player evaluation and assessment. Representative performance tests would enable coaches to objectively view kick difficulty and support a fairer assessment of player performance output through the incorporation of context in task design (Quarrie & Hopkins, 2015). For instance, if a player had three kicks during a game and only one was effective, their kicking efficiency would be rated at 33% and well below average, without any context provided. However, coaches need to consider the constraints placed on the individual kicks to ascertain whether all three kicks resulted from winning the ball from a stoppage, with the performer being under pressure and in possession of the ball for less than two secs, whilst making a short kick. Under these performance constraints an average value of expected kicking effectiveness would be 14.6% (Figure 4.4), offering a very different perspective on player performance.

Constraints interaction was measured with the rule induction approach which included five constraints, advancing the specification of rules in the study by Robertson et al. (2019), who included only three constraints. Despite these small methodological differences, the findings align with data observed within the elite AF competition level (Robertson et al., 2019). Confidence levels in effective kicks in both studies are within the 80-90% range and suggest that players perform better when kicking over shorter distances to an open target (e.g., an unmarked teammate or space on-field). Similar to findings reported by Robertson et al. (2019), the top five rules for effective kicks, are conducted under no pressure, from a kick < 40 metres and a majority from either a mark or a free kick. Within AF competitions, a mark and free kick are the only circumstances where possession can be taken without physical pressure being applied by the opposition. Conversely, for ineffective kicks, similar rules had a greater range in their confidence levels, ranging from 15% to 39% compared to the range of 38 to 45% in Robertson et al. (2019). This study revealed that the most common circumstances whereby an ineffective kick emerged was from possession sources related to open play situations. This observation combined with the short time in possession for ineffective kicks, could lead to speculation that players potentially do not have the skillset to gather or receive the ball under severe time constraints to kick effectively to a covered target (e.g., marked teammate or space). The differences between the findings of this study and other investigations of performance in AF may be due to a range of factors such as skill level, decision-making abilities, age and experience of the participant sample studied (Abernethy, 1988; Royal et al., 2006; A. M. Williams, 2000).

Understanding differences between tiers is crucial for creating a training design which is representative of the tier. Analysis of performance between tiers resulted in seven unique rules, four rules shared between two tiers and five rules found across all tiers (Figure 4.5). Of all ten

AFL rules identified by our methods, seven were found to be operative in either the state leagues or the U18 tier. Two of the three unique rules found in the AFL, included a kick target of a covered or leading player, which was found in only four rules produced by all three tiers. Kicking to a covered or leading target could be a more difficult kick to execute and, thus, it is somewhat unsurprising that they are found in two rules unique to the elite AFL competition. Between the U18 and state leagues tiers, greater variation exists in the nature of the seven shared rules. The state leagues were ranked more highly in four rules based on levels of confidence (Figure 4.5). Three rules contained constraints which come from an open play style of possession source (i.e., handball receive or groundball). Although conjecture, often in match conditions, these possession types have more pressure as they take place in dynamic, open play situations. The present findings are similar to those reported in other sports, where athletes from higher performance levels display improved skill performance outcomes compared to lower tiers (D. Smith et al., 1992). The ability to cope in these situations may be due to individual factors, including the age, learning, development and greater practice and performance experiences of these more skilled individuals (Renshaw et al., 2010). Incorporating individual constraints may also aid in understanding differences and development between sub-elite and elite players.

Understanding how athletes maintain their skill level under competitive performance conditions, and how this differs across performance tiers is essential knowledge for sports practitioners seeking to enhance the effectiveness and efficiency of training designs and transfer between practice and competition (Pinder et al., 2011; Pocock et al., 2018; Robertson et al., 2019). It is important to account for different performance tiers. This may help facilitates the adoption of targeted and representative training designs for athlete preparation and more closely aligned with developmental status, as opposed to attempting to use generic training designs which may be more suitable for athletes in other competitive performance tiers. As demonstrated in Figure 4.5 and as observed in differences with data reported by Robertson et al. (2019), the importance for accounting for influence of performance tier is vital to designing representative training environments. Differences in skilled performance exist at different tiers, potentially due to the changing prevalence and interaction of constraints. Thus, data obtained on performance from one tier cannot be transferred to the design of practice tasks for athletes in another competitive level due to specificity and representativeness of training designs. This observation emphasises the importance of understanding the specific athlete-environment interactions that occur in competitive performance conditions to develop a representative training designs (Pinder et al., 2011).

A rule-based approach may provide an objective tool to help quantify the level of representativeness within a practice task design which can complement existing subjective approaches, which rely on experiential knowledge of elite sport practitioners (Krause et al., 2018; Pocock et al., 2018; Robertson et al., 2019). This could improve the effectiveness and efficiency of designing training tasks which replicate competition environments, allowing them to target specific strengths and weaknesses within training, based on competition tier (Pinder et al., 2011; Robertson et al., 2019). This information could be used by coaches in multiple ways. First, they could seek to incorporate a constraints-led approach into their training design to create more challenging and realistic practice task designs where athletes are faced with these competition-environment constraints (Pinder et al., 2011). Alternatively, this type of design may afford opportunities for performers to experience a strategic effect on decision-making processes.

Given the increasing availability of larger datasets there is scope for future research to develop both team and individual-specific performance models to facilitate specificity of training designs. The power of these models could be enhanced by adding further constraints and contextual variables, such as such as physical output, field location and score margin of kicks to improve the predicted outcomes of skilled actions, and the representativeness of training designs (Ávila-Moreno et al., 2018; Royal et al., 2006). Feasibility of incorporating a large number of contextual variables and constraints into performance analysis can be limited due to challenges of interpreting large volumes of data in a time effective manner (Couceiro et al., 2016). Large datasets can impose some feasibility issues around data management. In the current study 5,060 (17%) kicks were missing a measurement for at least one of the seven constraints. Further, differences in sample sizes of kicks collected at each performance tier meant that some rules found in the smaller dataset had the potential to be more prevalent due to a bias from the competitive games analysed. Additionally, due to the manual treatment of discrete constraints, some constraints contained just two levels (i.e., kick distance) and others five (i.e., possession source), a potential for bias in rule frequencies exists due to the number of options within a specific constraint. Future research could use a continuous scale or fuzzy approaches to help account for this potential bias (Cariñena, 2014). Automated capture of data through deep learning and computer vision may aid in reducing time required and alleviate issues around manual data collection and interpretation (Couceiro et al., 2016; Robertson et al., 2019).

4.7 Conclusion

This study compared the variations in constraint interactions upon kicking action outcomes in AF across three different performance tiers. When effects of constraints are viewed in isolation, or pairs, they can offer some insight into what a player is experiencing in specific performance contexts. However, when all (or many) constraints are considered, a more complete picture can be provided. Rule induction provides a method capable of determining high frequency events and their outcomes. Findings from this analytics approach in research can be used to assess kicking performance of players, providing greater performance context to aid interpretation by practitioners. This information may then be used for player selection and recruitment purposes. The methodologies presented are not limited to kicking constraints, as sport specific constraints can be used to gain further understanding of performance conditions across a range of team sports. This analytics methodology may better inform and objectively define key events competitive performance which can be simulated in training and make using RLD more effective and efficient. Whilst there are specificities in differences between rules of AF and other team sports, the current findings cannot be transferred to other sports. However, the analytic methods presented here can be. Understanding how the interaction of constraints differs across performance tiers is vital to creating a representative design specific for player assessment and practice task composition for specific competitive performance tiers.

CHAPTER FIVE - STUDY III

Modelling the influence of task constraints on goal kicking performance in Australian Rules football

Chapter Overview

Chapter Five is the third of the four studies contained in this thesis. This study expanded upon Chapter Four by exploring improved methodologies to understand constraint influence in Australian Football. Three different analytical methods were applied to explore constraint interaction and influence on goal kicking. These techniques were compared for accuracy and useability.

This chapter contains a declaration of co-authorship and co-contribution (Section 5.1), an abstract (Section 5.2), introduction (Section 5.3), methods (Section 5.4), results (Section 5.5), discussion (Section 5.6) and conclusion (Section 5.7).

5.1 Declaration of co-authorship and co-contribution

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

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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Institute: Institute for Health and Sport Candidate's Contribution (%): 85

Status:

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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
Peter Ronald Browne Digitally signed by Peter Ronald Browne Date: 2020.10.08 15:57:05 +11'00'	08/10/2020

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

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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
5. The original data will be held for at least five years from the date indicated below and is stored at the following **location**(s):

All electronic data will be stored on the Victoria University R Drive. This is a secure central storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Alice Sweeting	5	Assisted with methodology design, feedback and revisions	[redacted]	8/10/20
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.		8/10/2020

Updated: September 2019

5.2 Abstract

Different analytical methods can aid increasing the understanding of competition environments and the influence of constraints on skilled events. The primary aim of this study was to determine the influence of task constraints on goal kicking performance in Australian football. The secondary aim was to compare the applicability of three analysis techniques; logistic regression, a rule induction approach and conditional inference trees to achieve the primary aim. In this study, task constraints related to shots on goal in the Australian Football League (AFL), such as shot type, field location and pressure, were measured. Logistic regression, Classification Based on Associations rules (CBA) and conditional inference trees were conducted to determine constraint interaction and their influence on goal kicking, with both the accuracy and interpretability of each approach assessed. Each model had similar accuracy, ranging between 63.5% and 65.4%. For general play shots, the type of pressure and location particularly affected the likelihood of a shot being successful. Location was also a major influence on goal kicking performance from set shots. When different analytical methods display similar performance on a given problem, those should be prioritised which show the highest interpretability and an ability to guide decision-making in a manner similar to what is currently observed in the organisation.

5.3 Introduction

It is well-established that sports performers are constantly exposed to a large number of constraints that manifest both concurrently and continuously. Constraints are variables which influence a system and shape the behaviour of an individual (Chow et al., 2007; K. M. Newell, 1986). They interact with each other non-linearly to influence skilled performance of both teams and individuals (Browne, Sweeting, et al., 2019; Pocock et al., 2018; Robertson et al., 2019). Typically, research has tended to isolate one or two key constraints as opposed to acknowledging these interactions. This has likely been due to the fact that many potentially influential constraints have not been measurable in a sufficiently valid or reliable manner (i.e., decision-making time and pressure, both physical and psychological). The importance of identifying key constraints has been highlighted (McCosker et al., 2019). However, improvements to technology has meant that many of these aspects are now feasibly measurable in many sports environments.

Another reason for the isolation of constraints in analysis has been either the inability or presumably lack of awareness of researchers to utilise analytical methods capable of describing the complexity inherent in constraint interactions in sports environments. Many machine learning algorithms have the ability to account for non-linear interactions of multiple variables (i.e., constraints) (Bunker & Thabtah, 2019). Furthermore, different analytical techniques may enable different outputs and visualisations of these constraint interactions. These consequently produce different opportunities for action by the end user, which may be more or less suitable depending on their intended purpose (i.e., training design, performance evaluation) or preferences. These outputs may relate to how the findings can be presented and interpreted, along with the specific type of decision that is recommend (i.e., recommendation or prediction).

Key stakeholders are most likely to use a model if its interpretability and functionality fits within the type of operational framework applied in that setting (Fernández et al., 2019).

Therefore, the design and style of the presentation of results is critical in guiding decision-making (Silver, 1991). Some complexity can be reduced by translating information into visuals, thus reducing the cognitive work required to interpret written reports (Kale et al., 2018). The application of findings may be supported by visualisations and increased practitioner education to have a positive impact in the sporting domain. Further, it could enable the incorporation of a more mainstream use of machine learning into performance evaluation in competition and training. Accordingly, this may facilitate a move away from a reductionist approach towards capturing and analysing multiple variables concurrently.

Australian Football (AF) is a complex invasion-style sport, played on an oval (length = ~ 160 m, width = ~ 130 m). A goal, worth six points, is scored by kicking a ball through two upright middle posts at the team's attacking end of the ground. A behind, worth one point, is scored by the ball going between the outer two posts (Australian Football League, 2016b; Gray & Jenkins, 2010). Accurate goal kicking has been identified as the most influential performance indicator of match outcome (Robertson, Back, et al., 2016). Despite this, limited research has explored how constraints interact to influence goal kicking performance in AF. The interaction of constraints has been explored in the Rugby Union place kick and shown to influence performance (Pocock et al., 2018).

The primary aim of this study was to determine the influence of environmental and task constraints on goal kicking performance in Australian football. The secondary aim was to compare the applicability of three analysis techniques; logistic regression, a rule induction approach and conditional inference trees to achieve the primary aim.

5.4 Methodology

Data was collected from all games (*n*=207) conducted in the 2017 Australian Football League (AFL) season. Data were obtained from Champion Data, who have not publicly released the validity and reliability of this data, however research has found very high levels of agreement between Champion Data and independent evaluation (Robertson, Gupta, et al., 2016). All shots on goal contained additional information such as shot type, shot outcome, pressure type and location. Pressure was manually collected by Champion Data based on the action and direction of opposing defender. Each variable had various sub-categories shown in Figure 5.1. The constraints used in this study are included in the official statistics provided to AFL clubs. A total of 9,725 attempted shots on goal were recorded; these were further split into set shots (n = 4,939) and general play shots (n= 4,786). The former refers to shots on goal which are directly preceded by either a mark or free kick, excluding where "play on" or "advantage" are called by the umpire. All other shots fit the category of general play. Further, shot location was divided into X (distance from goal) and Y (distance across the goal face). Distances were grouped in 10 m increments from 0 – 60 m in the X axis, and 10 m increments within 20 m across the goal face. Outside of 30 m they were grouped in 20 m due to the infrequencies of shots in these ranges (Figure 5.1 and 5.2). Ethical approval was granted by the University Human Research Ethics Committee (application number: HRE18-022).

Figure 5.1. **Breakdown of constraints for set and general play shots.**

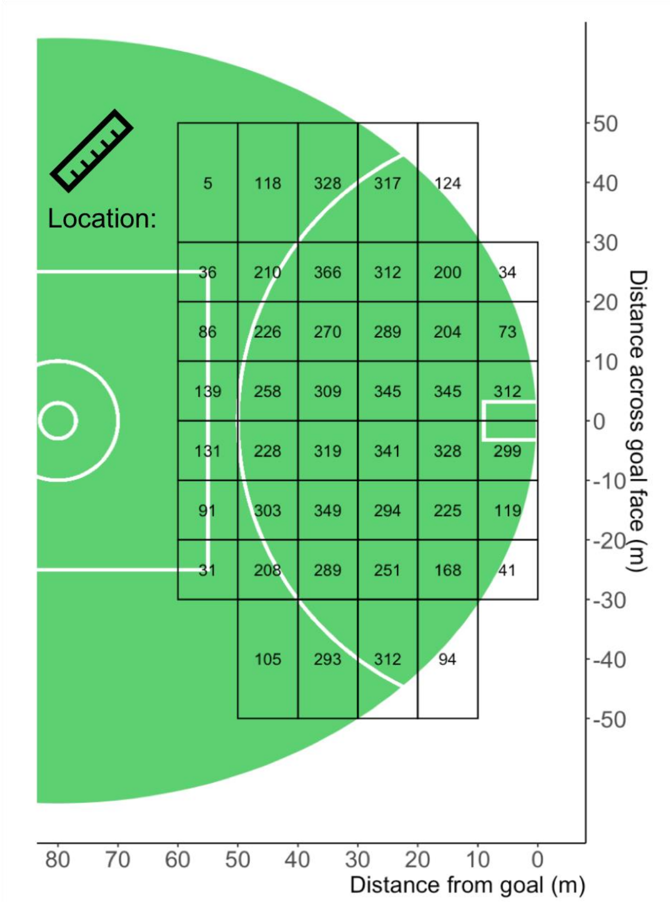

Figure 5.2. **Number of shots from each location for entire dataset.**

Nine models were developed using three techniques: logistic regression, a rule induction approach and conditional inference trees. These were chosen as, whilst they each treat shot outcome as a classification problem, they each consider independent variables differently and produce different outputs. The three techniques were run separately for all shots, set shots and general play shots, resulting in the generation of nine models. For all models, data were split into an 80% training set and a 20% testing set. All analyses were conducted in R (Version 3.1.2, R Foundation for Statistical Computing, Vienna, Austria). Model performance was defined by mean accuracy (%) between test and training datasets. Confusion matrices were also produced and levels of precision, recall and F1 were calculated for each model. Precision informs how accurate a model is at determining true positives from actual results. In comparison, recall measures the fraction of true positives from the predicted results. The F1 metric provides measured balance between precision and recall. For further information on calculating these metrics see Lipton, Elkan, and Naryanaswamy (2014).

Logistic regression is a mathematical modelling technique which is used to describe the relationship of several independent variables to a dependent variable (Atkinson & Nevill, 2001). This technique is widely used for the identification of variables which relate to sports performance, when working with a dichotomous dependent variables (Atkinson & Nevill, 2001). Logistic regression models considered the relationship between location, pressure and shot type constraints (independent variables) and the binary shot outcome, goal or no goal (dependent variable).

Rule induction is a branch of machine learning, capable of identifying underlying and frequent patterns between variables in a large transactional database (S. Morgan, 2011; Robertson et al., 2019; Spencer et al., 2016). The *Classification Based on Association rules* (CBA) algorithm, is an unsupervised data mining technique (Gentleman & Carey, 2008). The CBA algorithm was run in R, using the *'arulesCBA'* package (Johnson, 2018). A shot on goal was treated as the 'transaction', with the dependent variable specified as goal or no goal, and the constraints were used to describe it. Rules generated by the CBA algorithm were measured by their levels of *Support* and *Confidence,* see equation 2 and 3. Minimum support and confidence were set at 0.005 to allow for rules to be generated for each location bin where a shot took place. Where the minimum criteria were not met, no rule was generated and the output for that location was left blank. Outputs were limited to rules containing all relevant constraints for the set shot and general play model.

$$support(A => B) = P(A \cup B) \qquad \textit{Equation 2}$$

$$confidence(A => B) = \frac{support(A \cup B)}{support(A)} = P(B|A) \qquad \textit{Equation 3}$$

Conditional inference trees provide another non-linear approach to quantify the relationship between dependent variables (Corbett et al., 2017). They are a supervised machine learning technique which consist of a range of significance tests to determine a threshold for each dependent variable (Corbett et al., 2017; Sarda-Espinosa et al., 2017). Branches consists of a different combination of response variables, shot outcome, which leads to the prediction of the independent variable (Corbett et al., 2017). Conditional inference trees were generated using the *party* package in R (Hothorn et al., 2006). The algorithm functions on a predetermined level of statistical significance ($p < 0.05$), and factors which are most strongly linked with the response variable (goal or no goal) underwent recursive partitioning (Corbett et al., 2017; Sarda-Espinosa et al., 2017). Each tree was developed with a 95% confidence interval (CI) under a Bonferroni correction and a minimum terminal node size of 400 instances. The first tree was developed on the set shot dataset utilising two parameters, X and Y location. The second was run with the general play dataset and included four parameters, all constraint variables.

5.5 Results

Of the shots on goal attempted in the 2017 AFL season, mean shot accuracy was 50.4%. To understand how distance solely influenced shot success, the odds of success at each distance were calculated for width and length from the goal face (Figure 5.3).

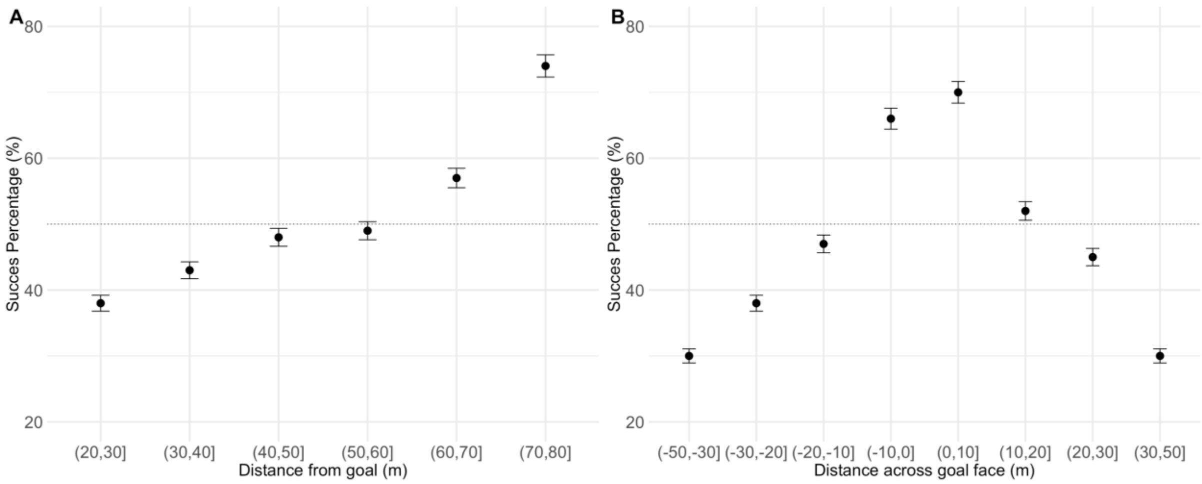

Figure 5.3. The mean success of shots on goal by location. Distance from the goal line in length (A) and distance across the goal face in width (B), where 0 is the centre of the goal. Confidence interval of 95% is shown. The horizontal dotted line represents the average success rate of a shot on goal.

Table 5.1. Confusion matrix and derived metrics for all shots in test dataset for each model.

		Actual					
		Logistic Regression		CBA		Conditional inference	
n = 1,941		Goal	No Goal	Goal	No Goal	Goal	No Goal
Predicted	Goal	846	146	383	566	491	458
	No Goal	526	423	143	849	232	760
Model mean accuracy		65.4%		63.5%		64.5%	
Recall		0.62		0.73		0.68	
Precision		0.85		0.40		0.85	
F1		0.72		0.52		0.76	

The three models showed similar levels of mean accuracy for all shots. Differences existed in levels of recall, precision and F1 (Table 5.1). The CBA model had the highest level of recall (0.73), however this was a trade-off given the low level of precision (0.40). Whereas, the logistic regression and conditional inference models showed a slightly lower recall value, 0.62

and 0.68 respectively, the precision value was higher at 0.85 for both, which resulted in a greater F1 value, 0.72 and 0.76 respectively (see Table 5.1).

The logistic regression model predicted shot outcome in the test dataset at 65.4% for all shots, 64.9% for set shots and 67.2% for general play shots. Both independent variables of X and Y locations impacted the outcome of set and general play shots. The four independent variables: X, Y, shot type and pressure were all correlated with the outcome of all shots based on the odds ratio (Table 5.2). For set shots only X-(10,20] had an odds ratio of less than one, 0.95. For general play shots two variables had an odds ratio of less than one, a pressure level of none and Y-(0,10], 0.81 and 0.93 respectively (Table 5.2).

Table 5.2. Logistic regression coefficients for set and general play shots

	Coefficients:	Estimate	SE	Z	OR	CI 95%	P-Value
General Play Shots	(Intercept)	-2.35	0.23	10.12			
	X - [0,10)	Ref					
	X - [10,20)	0.47	0.14	3.42	1.60	(1.22,2.09)	<0.01
	X - [20,30)	0.90	0.13	6.79	2.47	(1.90,3.20)	<0.01
	X - [30,40)	1.05	0.14	7.76	2.87	(2.20,3.74)	<0.01
	X - [40,50)	1.52	0.16	9.79	4.59	(3.38,6.22)	<0.01
	X - [50,60)	1.87	0.19	9.83	6.48	(4.47,9.41)	<0.01
	Y - (-10,0]	Ref					
	Y - (-20,-10]	0.74	0.12	6.21	2.09	(1.66,2.64)	<0.01
	Y - (-30,-20]	1.31	0.14	9.15	3.70	(2.79,4.89)	<0.01
	Y - (-50,-30]	1.70	0.20	8.61	5.47	(3.71,8.05)	<0.01
	Y - (0,10]	-0.08	0.11	-0.69	0.93	(0.75,1.15)	0.49
	Y - (10,20]	0.34	0.12	2.74	1.40	(1.10,1.78)	<0.01
	Y - (20,30]	0.98	0.13	7.41	2.65	(2.05,3.43)	<0.01
	Y - (30,50]	1.84	0.18	9.97	6.32	(4.40,9.08)	<0.01
	Mark Play On	Ref					
	On Run	0.60	0.16	3.72	1.83	(1.33,2.51)	<0.01
	Snap	1.21	0.17	7.14	3.34	(2.40,4.65)	<0.01
	Pressure - Chasing	Ref					
	Pressure - Closing	0.55	0.16	3.50	1.74	(1.28,2.37)	<0.01
	Pressure - Corralling	0.14	0.14	0.95	1.15	(0.86,1.52)	0.34
	Pressure - None	-0.22	0.16	-1.37	0.81	(0.59,1.10)	0.17
	Pressure - Physical	1.23	0.19	6.50	3.43	(2.36,4.97)	<0.01

Table 5.2. cont.

	Coefficients:	Estimate	SE	Z	OR	CI.95 %	P-Value
Set Shots	(Intercept)	-1.66	0.19	-8.55			
	X - [0,10)	Ref					
	X - [10,20)	-0.05	0.20	-0.26	0.95	(0.65,1.40)	0.8
	X - [20,30)	0.01	0.19	0.03	1.01	(0.70,1.45)	0.97
	X - [30,40)	0.24	0.18	1.32	1.28	(0.89,1.83)	0.19
	X - [40,50)	0.81	0.19	4.38	2.25	(1.57,3.24)	<0.01
	X - [50,60)	1.54	0.23	6.74	4.66	(2.98,7.28)	<0.01
	Y - (-10,0]	Ref					
	Y - (-20,-10]	1.03	0.14	7.30	2.81	(2.13,3.71)	<0.01
	Y - (-30,-20]	1.60	0.15	10.62	4.97	(3.70,6.69)	<0.01
	Y - (-50,-30]	2.19	0.15	14.27	8.98	(6.64,12.14)	<0.01
	Y - (0,10]	0.02	0.15	0.14	1.02	(0.76,1.37)	0.89
	Y - (10,20]	1.00	0.15	6.77	2.71	(2.03,3.61)	<0.01
	Y - (20,30]	1.44	0.14	10.08	4.23	(3.20,5.61)	<0.01
	Y - (30,50]	2.04	0.15	13.72	7.67	(5.74,10.27)	<0.01

The accuracy of the CBA model was 63.5% for all shots with an F1 of 0.52, and mean model accuracy for 63.8% for set shots and 63.3% for general play shots. The CBA algorithm produced differing numbers of rules which met the set criteria depending on the contextual variables selected. Confidence levels ranged from 0.18 to 0.99.

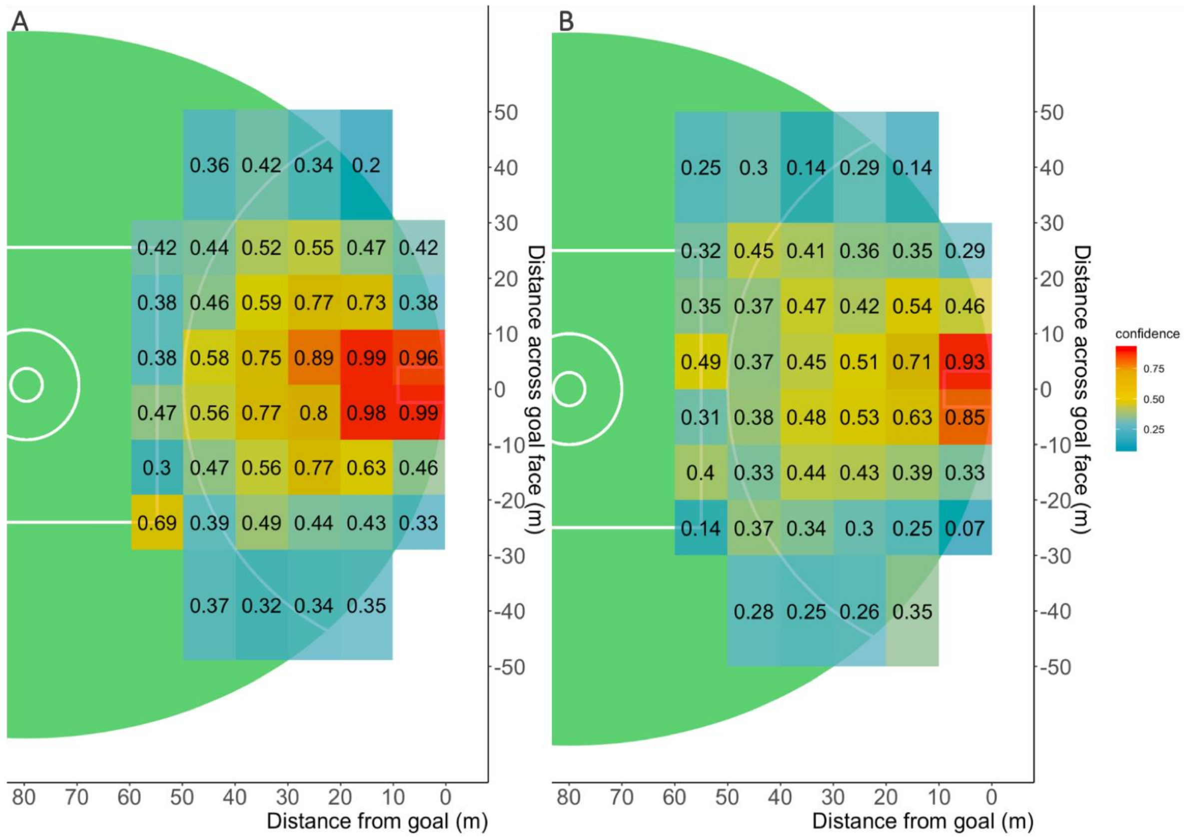

Figure 5.4. **Confidence levels for each bin based on CBA outputs. A) set shots, B) general play shots where the minimum criteria were met.**

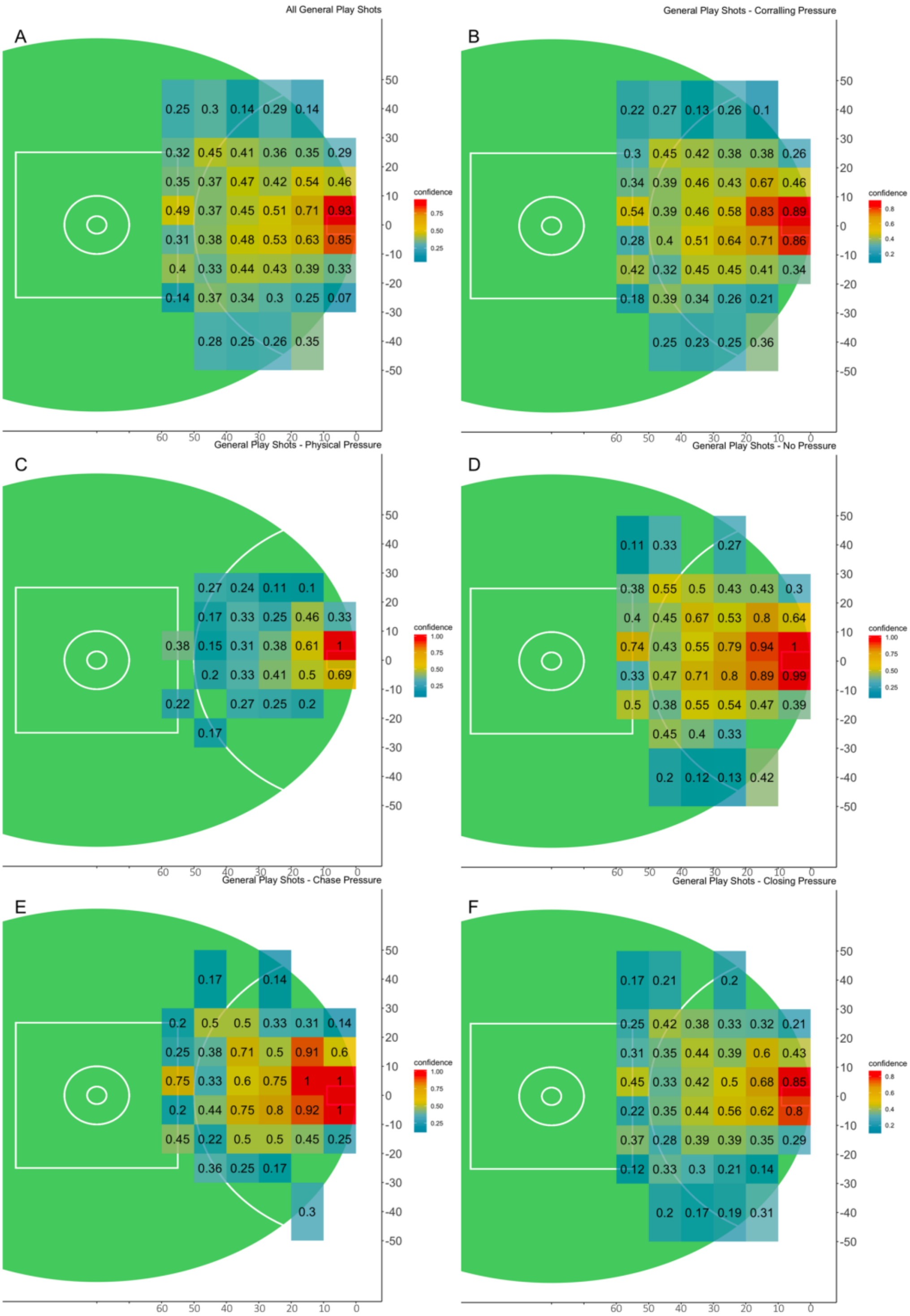

Figure 5.5. **Confidence levels for each bin based on different pressure types. A) All general play shots, B) shots under corralling pressure, C) shots under physical pressure, D) Shot with no pressure, E) Shots under chase pressure, F) Shots under closing pressure. Where the minimum criteria were met.**

Conditional inference trees predicted shot outcome with an F1 value of 0.76 and mean model accuracy of 64.5% for all shots, 64.7% for set shots and 64. 2% for general play shots. It revealed both X and Y locations to be strong indicators of shot success (Figure 5.6). For set shots the first partition was displacement in Y axis. The second partition was a further divide in the Y axis and displacement in X axis (Figure 5.6). The third and final level of partition was in the X and Y axis.

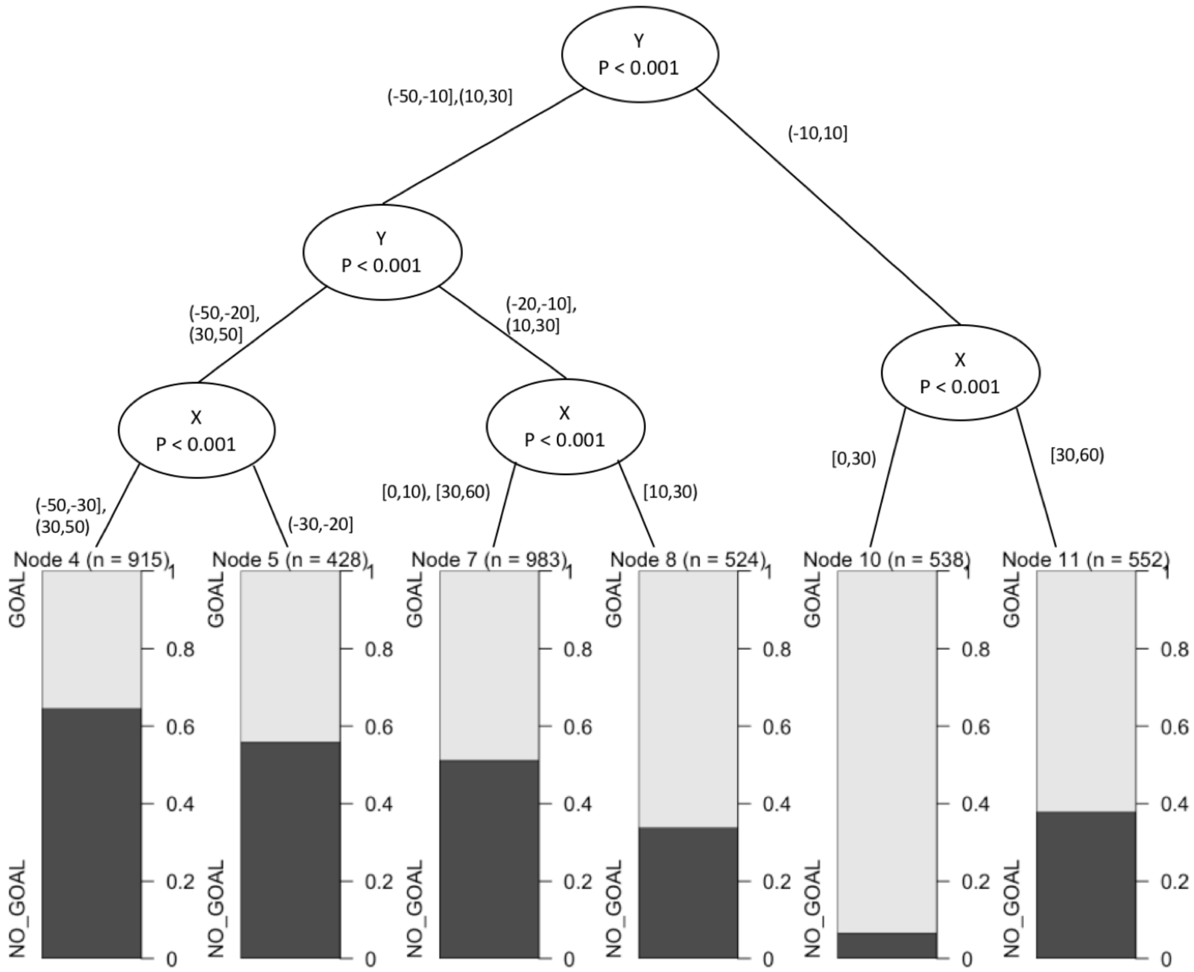

Figure 5.6. **Conditional inference tree for set shots. Location (X and Y axis) as the independent variable and shot outcome as the dependent variable.**

General play shots on goal also revealed that all independent variables were important factors in predicting shot outcome. The tree's first partition included Y displacement, with distance from goal and X and Y displacement forming the second split, and X displacement the final partition or alternatively by pressure level (Figure 5.7). Shot type did not form a split.

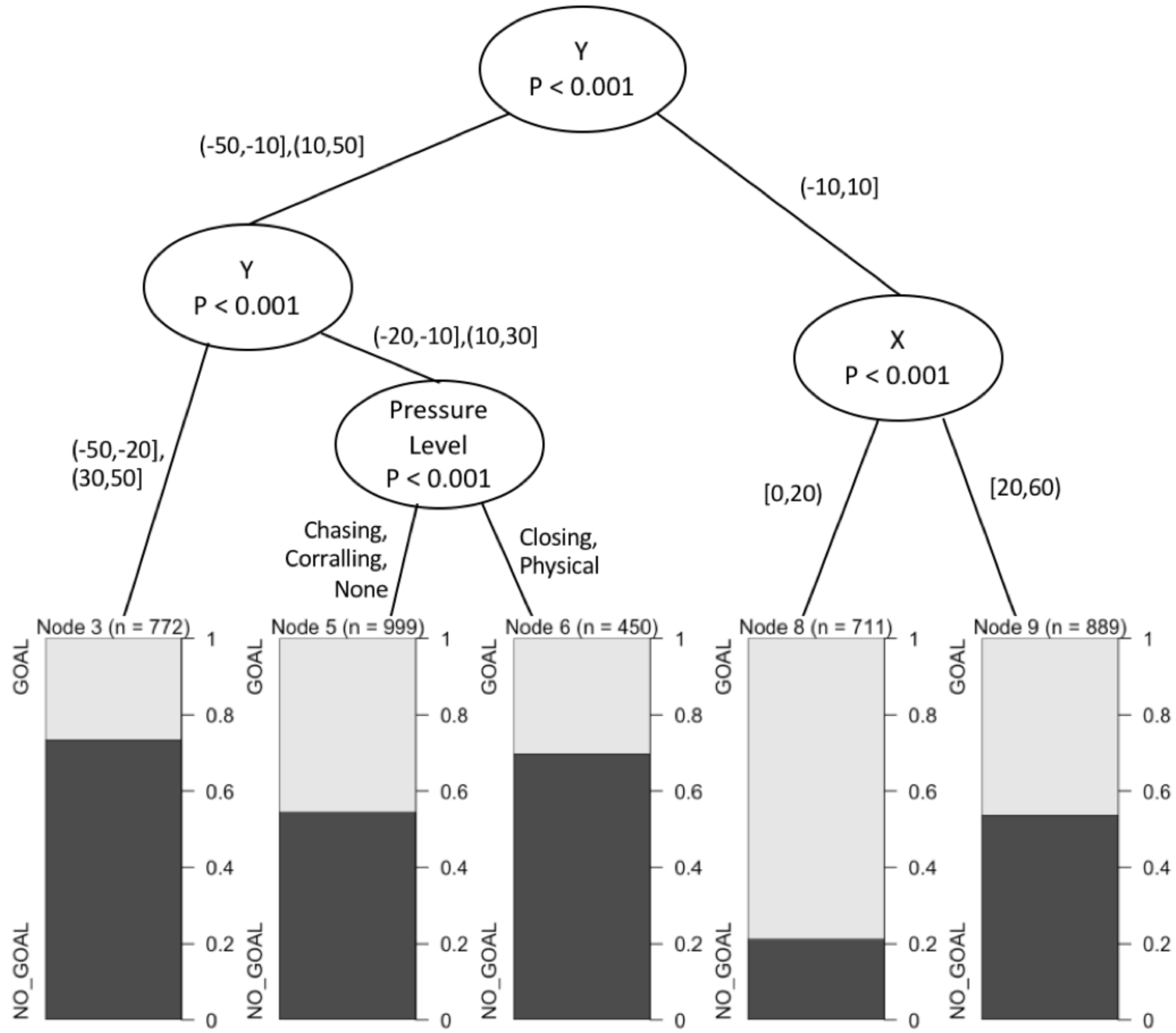

Figure 5.7. Conditional inference tree for general play shots. Location (X and Y), pressure type and shot type as the independent variables and shot outcome as the dependent variable.

5.6 Discussion

This study aimed to determine the influence of environmental and task constraints on goal kicking performance in Australian football. The study also compared the applicability of three analysis techniques: logistic regression, CBA and conditional inference trees. The different analysis techniques had similar accuracy levels. Given their similar performance, their interpretability and an ability to guide decision-making is essential for their use in the applied setting.

The measured constraints influenced shot outcome. The likelihood of scoring altered as location changed, this was demonstrated across every model (Table 5.2, Figure 5.2, 5.4-5.7). Two pressure constraints, corralling and none, had the least influence on goal kicking accuracy in the logistic regression model (Table 5.2). Both the logistic regression and conditional inference trees showed closing and physical pressure to have a negative impact on shot outcome (Figure 5.7). Further, shot type did not create a branch within the general play conditional inference tree (Figure 5.7). Location has also been identified as a significant predictor of kicking success in Rugby Union (Pocock et al., 2018). Furthermore, location and defensive pressure have been shown to influence shot outcome in basketball (A. Franks et al., 2015b; Goldsberry, 2012). Thus, irrespective of model visualisation each model suggests similar the patterns of influence.

The CBA and conditional inference trees (Figure 5.5-5.7) demonstrated the similarity between combinations of constraint types and likelihood of goal kicking accuracy. This concept has been referred to as “areas of equal opportunity” (Galbraith & Lockwood, 2010). These “areas of equal opportunity” should not only be calculated by location, but other key constraints such as physical pressure, score or previous kick success (Pocock et al., 2018). For example, it may be beneficial to move the ball wider and further from goal, to avoid taking a shot under physical pressure. This is shown in Figure 5.5C and Figure 5.5D were a shot under physical pressure from X (0,10) and Y(20,30) has a confidence level of 0.38 in contrast with a shot under no pressure from X(40,50) and Y(20,30) has a confidence level of 0.55. This information may be applied in educating athletes surrounding decision-making for shot selection.

For the logistic regression models, constraints differences are evident, however the interaction between constraints is difficult to observe. This model forces the user to look at constraints independently and without considering non-linearity in their interaction. In contrast, the CBA and conditional inference trees models allow for the interaction of constraints and their combined influence on goal kicking as a part of their inherent design. The logistic regression model was more accurate at predicting a goal, whereas in contrast the CBA and conditional inference models were better at predicting no goal (Table 5.1).

A benefit of the CBA and conditional inference tree techniques is their non-linear nature and visual output. Visualisations enable the improved understanding of data, leading to the ability to enable instinctive and effective knowledge discovery (Dadzie & Rowe, 2011). This is partly due to the decreased cognitive work required to interpret visualisations, as visuals take advantage of innate human perception (Dadzie & Rowe, 2011; Kale et al., 2018; Larkin & Simon, 1987).

Utilising multiple analysis techniques allowed for the demonstration of variation and importance in outputs and visuals. This is critical as findings may not be always be interpreted accurately and used effectively to inform decision-making (Couceiro et al., 2016; Le Meur & Torres-Ronda). Further, when providing results to coaches, their willingness to accept and apply findings is critical (Wright, 2015). Thus, a less accurate model, such as CBA which had the lowest F1 value, may be utilised over a slightly more accurate technique, due to the reduced complexity and higher interpretability of the model output. If results are too complex to interpret then the likelihood of the findings being implemented are minimal. It has also been suggested that appropriate staff should be embedded within professional clubs to aid in the statistical interpretation and applicability in industry settings, however producing analysis in practitioner friendly formats is also of use (Stewart et al., 2007).

The benefit of the models applied is the ability to account for further constraints in future models. This may include, exploring the game context such as time remaining and score margin as well as individual traits such as playing position and preferred foot (Clemente, Martins, & Mendes, 2016; Pocock et al., 2018). Additional data and the identification of key constraints which influence goal kicking could lead to more accurate models. This may help improve model accuracy to levels to make appropriate inferences from this data. Further data would enable the use of smaller bins to create more specific findings, as well as the potential to develop individual or team specific models. This would have a major impact in improving the accuracy and applicability of each model. Improved data capture may reduce subjectivity which currently exists in the measurement of currently collected constraints (for example see, Behendi, Morgan, and Fookes (2016), Nibali et al. (2017) and Victor, He, Morgan, and Miniutti (2017)). For instance, a constraint such as pressure, could be measured on a continuous scale or as via a density metric (Spencer et al., 2017a).

5.7 Conclusion

Constraint interaction has been shown to influence goal kicking in AF with differences between both set shots and general play shots, their location and pressure. Using the same dataset with different analysis techniques allows for varying outputs and visuals which demonstrated differences in feasibility of each model for the applied setting. Each methodology has different benefits, for instance the logistic regression explored each constraint individually and the independent influence of constraints is clear. Contrastingly, CBA and conditional inference trees can aid in identifying non-linear patterns more easily due to the ability to quickly visualise how multiple constraints interact together to influence shot outcome. Ultimately, preferences will come down to the individual user. This information may further the understanding of competition conditions may enhance current training design and enable the better preparation of players to meet competition demands.

CHAPTER SIX - STUDY IV

Application of a working framework for the measurement of representative learning design in Australian football

Chapter Overview

Chapter Six is the final of the four studies contained in this thesis. This study aimed to extend upon the previous chapters and attempted to present some methodological considerations to measure levels of representativeness between training and competition environments in Australian Football. Furthermore, this study aimed to determine the influence of preceding disposals on the current disposals effectiveness.

This chapter contains a declaration of co-authorship and co-contribution (Section 6.1), an abstract (Section 6.2), introduction (Section 6.3), methods (Section 6.4), results (Section 6.5), discussion (Section 6.6) and conclusion (Section 6.7).

6.1 Declaration of co-authorship and co-contribution

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

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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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.

[redacted] 8/10/2020

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

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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;

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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
Alice Sweeting	5	Assisted with methodology design, feedback and revisions	[redacted]	8/10/20
Carl Woods	5	Assisted with positioning theoretical framework, feedback and methodology		8/10/20
Sam Robertson	10	Assisted with conceiving study design. Manuscript feedback and revisions.		8/10/2020

Updated: September 2019

6.2 Abstract

Representative learning design proposes that a training task should represent informational constraints present within a competitive environment. To assess the level of representativeness of a training task, the frequency and interaction of constraints should be measured. This study compared constraint interactions and their frequency in training (match simulations and small sided games) with competition environments in elite Australian football. The extent to which constraints influenced kick and handball effectiveness between competition matches, match simulations and small sided games was determined. The constraints of pressure and time in possession were assessed, alongside disposal effectiveness, through an association rule algorithm. These rules were then expanded to determine whether a disposal was influenced by the preceding disposal. Disposal type differed between training and competition environments, with match simulations yielding greater representativeness compared to small sided games. The subsequent disposal was generally more effective in small sided games compared to the match simulations and competition matches. These findings offer insight into the measurement of representative learning designs through the non-linear modelling of constraint interactions. The analytical techniques utilised may assist other practitioners with the design and monitoring of training tasks intended to facilitate skill transfer from preparation to competition.

6.3 Introduction

A predominant challenge facing sports practitioners is the design and implementation of training environments that represent competition. This approach to training design has been referred to as representative learning design (RLD) (Pinder et al., 2011). Theoretically, RLD advocates for training to consist of key (informational) constraints that are experienced within competition to maximise the transfer of skill from training to competition (Brunswik, 1956; Pinder et al., 2011). Constraints are categorised into Individual (e.g., physical attributes and emotions), Task (e.g., rules and ground dimensions) and Environmental (e.g., weather and gravity) classes (Davids et al., 2008; K. M. Newell, 1986). To assist with the design of representative training tasks, practitioners typically record the constraints of a competitive environment to ensure such constraints are designed into training (Woods, McKeown, Shuttleworth, Davids, & Robertson, 2019). However, understanding how these constraints interact to influence a performer's actions and behaviours is an ongoing challenge for practitioners given the non-linearity and dynamicity of sports performance (Robertson et al., 2019).

An important feature of a constraints-led approach to training design is the understanding that constraints do not exist in isolation. Rather, they dynamically interact with one another, often in a continuous manner (Araújo & Davids, 2018; Davids et al., 2008). However, the measurement of the dynamic interaction of constraints has been somewhat neglected within the literature (Robertson et al., 2019). Whilst constraints can be collected from training and competition environments, such approaches often overlook constraint interaction and are unable to capture then analyse the complexity of systems in full (McLean et al., 2019; Vaughan et al., 2019). Recently, the interaction among constraints was examined via machine learning techniques in Australian football (AF) (Browne, Sweeting, et al., 2019; Robertson et al., 2019). The application of a rules-based approach enables the complexity of RLD to be measured, through the identification of key constraint interactions based on both their frequency and their displayed influence on behaviours. An informed RLD is vital for practitioners, as how constraints are enacted in training implicates skill development and learning transfer (Araújo et al., 2004; Handford et al., 1997; Pinder et al., 2011; Pocock et al., 2018).

Within many team sports, including AF, small sided games (SSGs) are used as a frequent training modality due to their perceived representativeness of competition matches and ease of constraint manipulation (Canton et al., 2019; Ometto et al., 2018). Specifically, SSGs can be used to simulate sub-phases of competition, whilst to some extent, preserve the complex interactions between an athlete and their environment (Aguiar, Botelho, Lago, Maças, & Sampaio, 2012; Gonçalves et al., 2017; Hristovski, Davids, Araújo, & Passos, 2013). Match simulations are another common training strategy within preparation for performance models in team sports, as they afford practitioners with a practice landscape that can simulate scenarios commonly encountered within competition. Match simulations and SSGs are different types of training modalities and thus, the frequency and interaction of constraints may differ. The intent of these training modalities are different, and as such, their use within the broader training schedule should be carefully considered by coaches (Farrow & Robertson, 2017).

The primary aim of this study was to compare constraint interactions and their frequencies, between match simulations, SSGs, and competition matches in AF. These comparisons were facilitated using a rule-based algorithm. Secondly, the study aimed to determine the extent to which they influenced disposal type and effectiveness. Thirdly, this study sought to understand the sequential nature of disposals by examining whether the efficiency of a disposal was influenced by the preceding disposal. By addressing these aims, this study sought to progress the methodology of measurement for RLD in sporting environments.

6.4 Methodology

Data were collected from official matches and training sessions from one Australian Football League (AFL) club across the 2018 and 2019 (pre)seasons. All 2018 regular season matches were included (n = 22, disposal instances = 3,478). Specific tasks from training sessions were included, consisting of match simulations (n = 13, disposal instances = 1,298) and SSGs (n = 24, disposal instances = 2,677). Seven versions of SSGs were included ranging from seven to 18 athletes. Ground dimensions ranged from approximately 20 x 20 m to 60 x 60 m. Number inequalities were included in some SSGs, with the largest discrepancy between team numbers being three additional attackers compared to defenders. Given the applied nature of this research, these design features were hard to control. Ethical approval was granted by the University Human Research Ethics Committee (application number: HRE18-022), and written consent was gained from the organisation to use de-identified data as collected per regulation training practices.

Match footage was provided by Champion Data (Melbourne, Australia, Pty. Ltd.), whilst training tasks were filmed by club staff from the same perspective as the competition match footage (behind the goals and side view). All footage was then subjected to notational analysis via SportsCode (version 11.2.3, Hudl). The lead author and a performance analyst coded all footage using a code window developed with a weighted kappa statistic of >.80, indicating very good reliability (Back, 2015). Constraints collected included: disposal type, pressure, time in possession and disposal effectiveness (Table 6.1). These constraint types were based upon similar literature (Browne, Sweeting, et al., 2019; Ireland et al., 2019; Robertson et al., 2019). The nature of the options for each constraint sampled limited bias in the rule-based approach, as all constraints had the same number of sub-categories (Table 6.1).

Table 6.1. Description of constraints sampled, their sub-category, and definition

Constraint sampled	Sub-category	Definition
Disposal Type	Kick	Disposal of the football with any part of the leg below the knee
	Handball	Disposal of the football by hitting it with the clenched fist of one hand, while holding the football with the other
Pressure	Pressure No Pressure	Opposition player defending the ball carrier from any direction
Time in Possession	> 2 sec < 2 sec	Time with ball in possession from receiving the football to disposing of it
Disposal Effectiveness	Effective Ineffective	An effective kick is of more than 40 m to a 50/50 contest or better for the team in possession, or a kick of less than 40 m that results in retained possession

All analyses were undertaken in the R computing environment (version 3.6.1, Vienna, Austria) and included a three-stage process. All code for the following analyses are available on GitHub (www.github.com/PeterRBrowne). First, association rules were generated for all disposals for match simulations, SSGs and competitive matches. Association rules are a type of machine learning algorithm which can identify underlying and frequent non-linear patterns in a large dataset (S. Morgan, 2011). The '*Arules*' package was used to apply the Apriori algorithm (Hahsler et al., 2018) and to measure the association between multiple constraints on disposal efficiency. Minimum support and confidence levels were set at 0.0002 to allow for all possible rules to be generated. The minimum number of variables was set at four to ensure that each coded constraint was included. The association rules were arbitrarily assigned an alphabetical identity (ID), being then compared by levels of support and confidence (Browne, Morgan, et al., 2019).

The frequency with which a rule occurred and was then followed by a subsequent rule was then calculated using the *'tidyr'* and *'dplyr'* packages (Wickham, Francois, Henry, & Müller, 2015;

Wickham & Henry, 2018). The difference between training and competition frequencies was then calculated. The observed frequency of a third disposal being effective was calculated. This was visualised using a lattice plot, with colour hues to differentiate the observed frequency of an effective disposal. The level of observed frequency of an effective disposal was calculated as the weighted average of the confidence of a Rule ID and the frequency with which three sequential rules occurred.

6.5 Results

The association rules with assigned alphabetical ID are presented in Table 6.2, and the differences in rule frequency (A) and confidence levels (B) are displayed in Figure 6.1. The lowest support across all three environments was Rule E (0.012), and the largest was Rule G (0.316), with both occurring in the competition environment (Figure 6.1A). The support levels for match simulation rules were generally more representative of a competitive match, relative to SSGs, based on the constraints measured. Rule G, a pressured handball performed within 2s, showed the largest difference between competition matches and the SSGs (Figure 6.1A). Levels of support also varied between environments, with Rule G being the most frequent in matches and match simulations, whilst Rule D was the most frequent in SSGs (Figure 6.1A). With the exception of Rule C, rules corresponding to 'kicks' yielded lower confidence in competition matches relative to SSGs, but higher confidence relative to match simulations (Figure 6.1B). For rules relating to 'handballs', the confidence was highest in competition matches relative to the training tasks (Figure 6.1B).

Table 6.2. Breakdown of each possible association rule and its associated alphabetical ID

ID	Type	Pressure	Time in Possession (seconds)
A	Kick	No Pressure	<2
B	Kick	No Pressure	>2
C	Kick	Pressure	>2
D	Kick	Pressure	<2
E	Handball	No Pressure	>2
F	Handball	No Pressure	<2
G	Handball	Pressure	<2
H	Handball	Pressure	>2

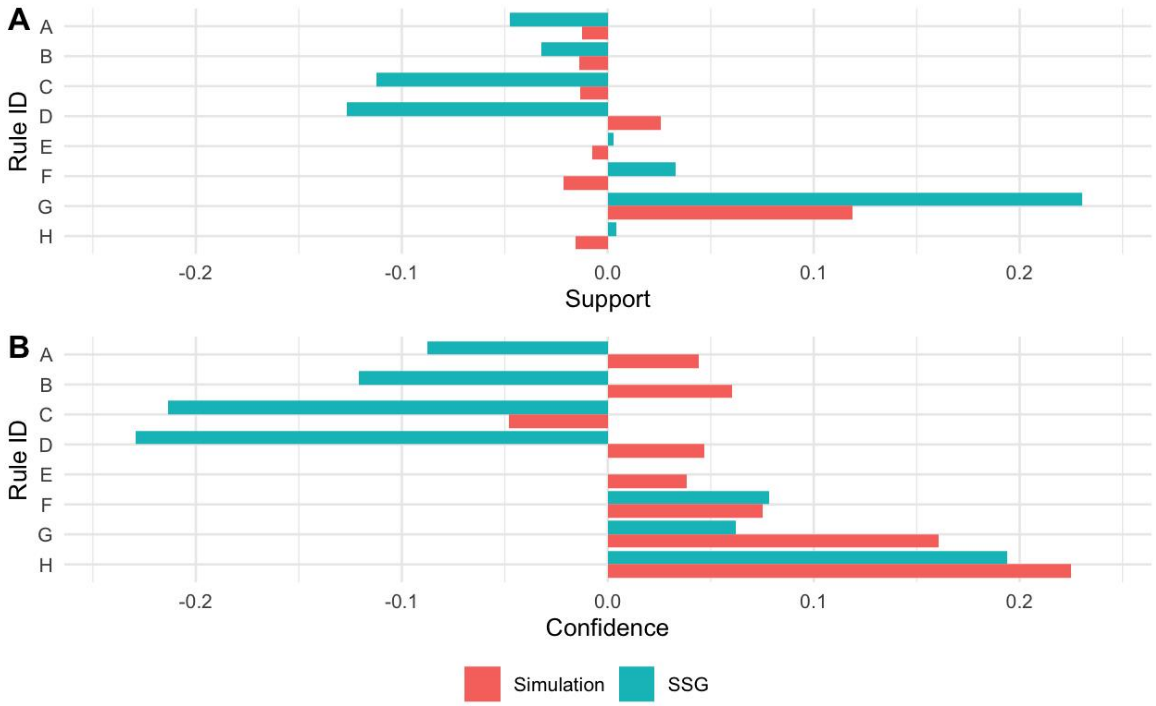

Figure 6.1. **Variation in levels of support (A) and confidence (B) of each Rule ID match simulations and Small Sided Games relative to competition matches. Where zero is equal to competition matches. Positive values reflect greater values for competition matches.**

The differences between sequential Rule IDs were calculated between training and competition environments (Table 6.3). Positive values reflect a greater frequency of occurrence within competition matches, whereas negative values indicate greater frequency of occurrence in the training environment. Match simulations were more similar to competition matches, relative to SSGs in levels of support (Table 6.3A) and confidence (Table 6.3B). Disposal sequence differed more between competition matches and SSGs, with eight sequences having a greater than a ±20 % difference between environments (Table 6.3B). Whilst for similar disposal sequences between training and competition environments, both match simulation and SSGs were similar with twelve and eleven sequences having less than ±1 % difference respectively (Table 6.3).

Table 6.3. **Difference between frequency of second pass following first pass for competition matches and match simulations (A), and competition matches and SSGs (B). Values are expressed as percentage differences (%).**

A		Second Pass							
		A	B	C	D	E	F	G	H
First Pass	A	-2	9	3	2	1	-6	-6	-2
	B	4	-18	2	9	-3	-3	11	-2
	C	0	7	-9	5	0	-2	1	-2
	D	-1	5	-11	2	0	-4	12	-4
	E	3	-18	13	0	NA	8	0	-5
	F	-2	-7	0	6	0	3	3	-3
	G	-7	1	2	-1	-1	-4	11	-2
	H	-8	-3	-2	0	0	-2	23	NA

B		Second Pass							
		A	B	C	D	E	F	G	H
First Pass	A	-18	4	-4	-7	3	6	16	1
	B	-4	-24	0	6	0	0	23	-1
	C	-3	19	-22	-26	0	3	28	2
	D	-1	13	-20	-26	0	4	28	1
	E	2	-8	-4	2	NA	8	2	-2
	F	-7	-2	-1	0	-1	-2	12	0
	G	-2	4	-2	3	0	-3	2	-3
	H	-3	-3	-3	-19	0	5	26	NA

Note: **Greater negative values (the deeper the orange hue) indicate greater frequency of the rule sequence in the training environment. Larger positive values (the deeper the blue hue) indicate a greater frequency of the rule sequence in the competition environment. *NA* represents where the two rule IDs did not occur sequentially. Values closer to '0' denote closer similarities between training and competition.**

Figure 6.2 depicts the observed frequency of effectiveness of the third disposal following two sequential disposals across competition matches (A), match simulations (B) and SSGs (C). The variation between competition and training environments are visualised through colour hues, in addition to the observed frequency being overlayed. The third disposal in the sequence was more likely to be effective in SGGs, relative to competition matches and match simulation. Specifically, the observed frequency of the third disposal in the sequence being effective ranged from 54 to 89% for competition matches, 49 to 84% for match simulations, compared to 77 to 88% for SSGs (Figure 6.3). A majority of competition match third disposal effectiveness were above 70%, with only six disposal sequences less than 70% effectiveness. Comparatively, 28 disposal sequences during match simulations resulted in less than 70% effectiveness (Figure 6.2, 6.3).

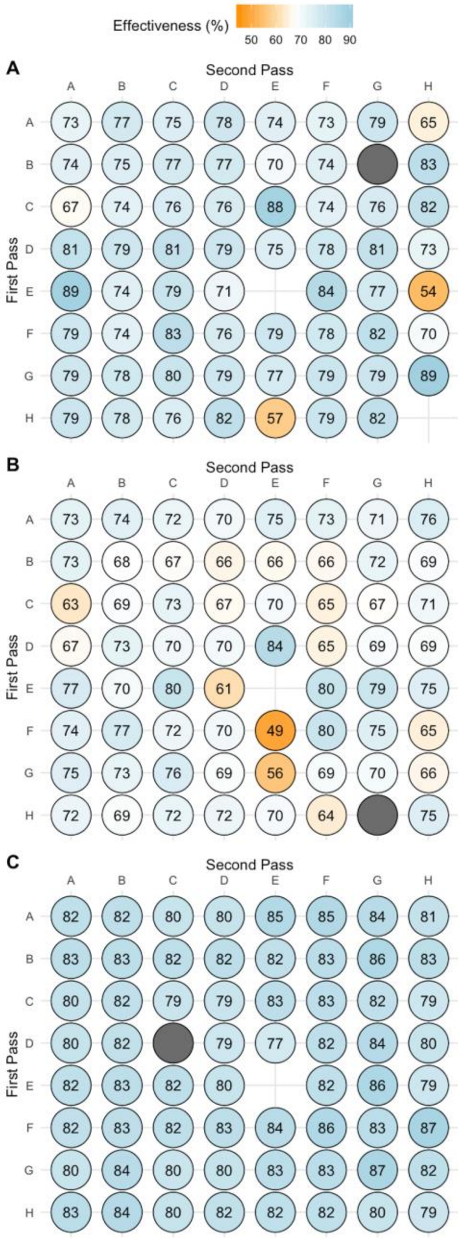

Figure 6.2. **The observed frequency of effectiveness of the third disposal following two sequential disposals across competition matches A) competition match B) match simulation C) Small Sided Games. Values expressed as percentages (%).**

Note: **The scale moves from orange to blue with the deeper the hue the greater observed frequency of an effective third disposal. Blank sections are those which did not have two sequential passes. Grey circles reflect those sequences of passes which did not continue to a third disposal.**

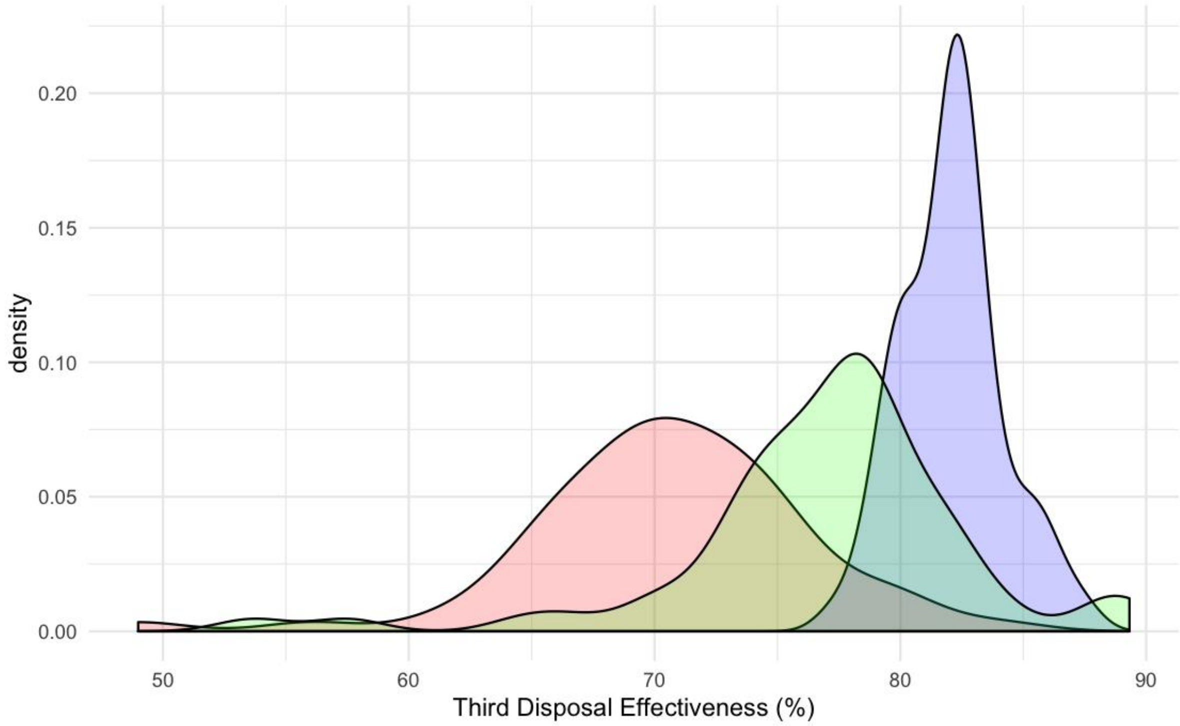

Figure 6.3. Density plot of the observed frequency of effectiveness of a third disposal following the two previous disposals across competition matches (green), match simulations (red) and Small Sided Games (blue).

6.6 Discussion

The primary aim of this study was to compare constraint interactions and their frequencies between match simulations, SSGs, and competition matches in AF using a rule-based algorithm. Secondly, it aimed to determine the extent to which they influenced disposal type and effectiveness. Thirdly, this study sought to understand the sequential nature of disposals and whether disposal sequences are dependent upon the preceding disposals. Accordingly, this study aimed to progress the methodology for the measurement of RLD beyond recording a single instance and to account for continuous nature of match events and the constraints impacting them. For instance, by extending the rule-based approach from exploring a single disposal as in Browne, Sweeting, et al. (2019), this study sought to understand disposal sequences, and the extent to which disposals are dependent on preceding disposals. Results demonstrated that the frequency and confidence of different disposal types and constraint interactions varied between match and training environments. These differences varied depending on the training task, with match simulations yielding a greater level of representativeness to matches relative to SSGs. However, the level of representativeness and intent of each SSG may differ the efficacy of each approach may vary depending on the given context.

With respect to the primary aim, this study demonstrates that an understanding of the differences between support and confidence levels of constraint interactions within training and competition environments is an important consideration for the design of representative training tasks. For example, match simulations generally showed greater similarity to competition matches, with respect to disposal type. However, competition matches incurred a greater frequency of pressured handballs performed within 2s (Rule G), relative to match simulations. These differences between training and competition environments could exist for a number of practical reasons. Notably, the design features of the SSGs could intentionally favour a specific disposal type (e.g. kick), whilst, in general, the training environment could incur less physical pressure relative to a competitive match, given differences in physical exertion and intensity (Ireland et al., 2019). Practitioners may therefore use this information to better understand the influence of constraints on performance, which could, improve the representativeness of such training tasks through informed manipulation, such as increasing (or decreasing) playing area dimensions to encourage differing levels of pressure on disposals (Almeida et al., 2012; Klusemann et al., 2012). Moreover, this study provides a methodology to better understand the design of training tasks that may aid practitioner decision-making in implementing appropriate SSGs for their desired intent.

Due to the intent of the match simulations compared to SSGs, it is unsurprising to note that match simulations were more representative of competition compared to the SSGs. Thus, it is reasonable to suggest that not all training tasks will yield the same level of representativeness, potentially due to their explicit intent. For example, a practitioner may manipulate certain constraints of a SSG to facilitate greater disposal efficiency, reducing representativeness relative to competition, but still achieving the intended task goal. Conversely, a practitioner may want to challenge disposal efficiency within a SSG by manipulating temporal and spatial constraints so the training task is harder (with reference to time and space) than what is afforded within competition. Although it is likely that practitioners' do not plan for every training task to express near perfect representativeness, this methodology provides a platform by which 'target' areas could be identified, informing practitioners as to how frequent non-representative actions are performed within practice. Such information could better guide the macro- and meso-structures of practice, ensuring less representative training tasks are coupled with more representative tasks. Further, this aligns with the principles of periodisation for skill acquisition (Farrow & Robertson, 2017), emphasising the importance of being able to measure the influence of constraint interaction within training tasks (Browne, Sweeting, et al., 2019). A training task classification systems may be able to aid practitioners in this process to ensure the appropriate tasks are conducted together based on its characteristics and intent (Corbett et al., 2018). However, the ideal balance of representative versus non-representative practice to gain the greatest performance benefit in competition, is currently unknown.

The third aim sought to explore concomitant disposal sequences. Differences between the training and competitive performance environments were found when exploring the observed frequency of a third sequential disposal being classified as 'effective'. Understanding disposal sequences is a key feature of complexity. This is essential for RLD as it enables understanding of not just the current status, but which interactions occur after. For matches and match simulations, the observed frequency of an effective third sequential disposal was lower compared to the SSGs. This practice task yielded the highest range of observed frequency for an effective third disposal, likely due to the task design of the SSGs, which may encourage a more continuous, effective, chain of disposal. This could have been intentionally designed within the SSGs through the systematic manipulation of player numbers (task constraint) to favour the offensive team (for example, a SSG consisting of 6 vs. 4). Nonetheless, this analysis demonstrates how a chain of disposals could partially shape future disposal effectiveness, thus providing some evidence that the effectiveness of a disposal may not be independent from preceding events.

A limitation of this study was that it grouped all SSGs together, despite it being possible that some SSGs had differing task intentions and subsequent challenge points, diluting their representativeness. Accounting for intent in SSGs may allow for a more complete insight into their representativeness relative to competitive matches. Future research can look to apply the methodological advancements from this study to further understand the differences between various SSGs. Additionally, a limited number of constraints were used to model RLD, and thus the model presented here is a truncated view of RLD. The sampling of appropriate constraints is an evolving process, as better and new measures become available. The use of experiential coach knowledge could aid in the informed selection of constraints, however experiential knowledge is dependent on the individual, subject to biases and the environment in which it is applied. Further, this study focused solely on the ball carrier, with it being likely that other constraints, such as opposition and teammate location and the individual's action capabilities, additionally influenced the disposal outcome. Models that consider these factors will likely further explain disposal effectiveness, but their performance must be considered against any decrease in interpretability that may arise from the utility of larger constraint sets. Additionally, future studies could look to examine the frequency of rule occurrence in a defined period of time (Ireland et al., 2019). For instance, a SSG played in a small area may have a higher frequency of disposals per minute, compared to a larger area.

6.7 Conclusion

Disposals are influenced by the interaction of constraints in training and competition environments in elite AF. Variation exists in the frequency whereby disposals occur under specific constraints across the competition matches, match simulations and SSGs. Although training and competition environments differed, this study found greater levels of representativeness existed between match simulations and competition matches compared to the grouped SSGs and competition matches. These insights can aid the comprehension of how constraints interact to shape the emergence of specific disposals and their effectiveness, affording practitioners with a platform for the development and measurement of representative training tasks. The analytical techniques applied in the present study are not limited to AF and may assist in designing representative training tasks across other sports via the consideration of constraint interaction. Importantly, this study provides a methodological advancement in the measurement of constraint influence, frequency and accounting for the continuous nature of sport.

CHAPTER SEVEN - GENERAL DISCUSSION AND CONCLUSION

Chapter Overview

This final chapter consolidates the key findings and implications of this thesis and discusses how these can be implemented in the applied setting. This chapter contains a general discussion (Section 7.1), industry implementations (Section 7.2), future directions (Section 7.3), and conclusions (Section 7.4).

7.1 General Discussion

This thesis aimed to extend upon traditional performance analysis practices through the development and implementation of methodologies grounded in ecological dynamics and applied using machine learning techniques. These methodologies were applied with the aim to better measure the interaction and influence of constraints on skilled behaviour in sport. The sport of Australian Football (AF) was used as an exemplar. An ecological dynamics approach was used to explore how developments in fields such as technology, analytics and the perceptual sciences could aid an interdisciplinary approach to sports performance research (Chapter Three). The interaction and influence of multiple constraints on field kicking in AF was demonstrated, and also compared between different competition tiers (Chapter Four). Furthermore, the interaction of constraints in goal kicking was measured using multiple machine learning techniques, which offered different outputs respective to each technique (Chapter Five). Importantly, methodological improvements were made to account for the sequential and complex nature of sport through the application of an ecological dynamics rationale (Chapter Six). The differences between the frequency and influence of constraints in the training and competition settings were also demonstrated (Chapter Six).

An interdisciplinary approach with an underlying theoretical framework of ecological dynamics, may improve the impact of sport science in research and applied settings (Chapter Three). The benefits of an interdisciplinary approach arise from greater consistency between disciplines, leading to more efficient workflows and optimised communication procedures (Balagué et al., 2017). These improvements may allow for the development of additional opportunities and an increased ability to answer questions more completely, rather than being limited to solutions that have origins and applications in a single discipline. Interdisciplinarity may provide an approach to shift away from the current siloed and reductionist style of analysis (Rothwell et al., 2020; Springham, Walker, Strudwick, & Turner, 2018). Furthermore, by embracing an interdisciplinary approach, new progress could be realised for many of sport science’s most pervasive and important questions, from how to get the best transfer from training to competition, to injury prediction and predicting an athletes future performance. Machine learning techniques, paired with ecological dynamics, may allow for a more symbiotic relationship between sport science disciplines in research and the applied setting, thus aiding the transfer between disciplines.

Performance analysis has traditionally recorded and analysed the *who, when* and the *what* of events (McGarry, 2009; Vilar, Araújo, Davids, & Button, 2012). However, performance analysis has not typically explored the *how* and *why* of an event. As highlighted in this thesis, observing performance through a theoretical framework may help to account for the *how* and *why* of events, as it structures the analysis around both the individual and the environment (McCosker et al., 2019; McGarry, 2009). For example, in AF, the outcome of a kick is currently defined as effective or ineffective, which does not convey all the relevant information to critically evaluate a kick. An understanding of the constraints acting on a kick, such as pressure or kick distance, may help inform *how* and *why* that kick was effective or ineffective (Chapter Four). Applying a theoretical framework also enabled an insight into the *how* and *why* goal kicking was effective or ineffective (Chapter Five). In addition to the influence of constraints on a disposal, the preceding sequence of events also influence *how* and *why* a disposal is effective or ineffective (Chapter Six). This thesis explored the influence of constraints and the sequence of events on skilled performance in AF. The identification and analysis of key constraints may help guide the design of training drills and match analysis (McCosker et al., 2019).

The majority of research on constraints in sport has been theoretical or conceptual in nature (Araújo et al., 2009; Couceiro et al., 2016; Davids et al., 2012; Davids et al., 2003; Davids et al., 2013). Moreover, when constraints have been used to summarise and quantify player performance in the applied setting, it has typically been through a uni- or bi-variate analysis approach (Back, 2015; Pocock et al., 2018). However, a potentially infinite number of constraints are acting on individuals and teams during competition and training (Davids & Araújo, 2010). Although it is not feasible to measure all relevant constraints, the use of multivariate analysis techniques helps to better understand how multiple constraints interact to influence player performance. This may therefore go some way to improving the understanding of these environments and better quantifying player performance. For example, Figure 4.6 in Chapter Four, demonstrates how the average field kicking efficiency varies as more constraints are included in the analysis. Chapter Four therefore applied a rule-based approach to analyse five constraints acting on AF kicks to determine their interaction and influence on kicking effectiveness. The information from this methodology was used to compare and understand the variance in the influence of constraints between competition tiers. The rule-based approach showed AFL players had a higher kicking effectiveness within most groupings of constraints compared to the U18 and state tiers (Chapter Four). A rule-based approach can therefore quantify the variance in player skill across tiers. This method could be used to encourage an interdisciplinary approach between departments. Whilst Chapter Four applied a rule-based approach, other analytical approaches can be applied to understand the influence of constraints on skilled performance.

Three different analytical approaches were applied in Chapter Five to explore the influence of multiple constraints on AF goal kicking as a binary outcome measure (successful or non-successful). Each of the three methodologies had different benefits. The logistic regression model treated each constraint individually and the independent influence of each individual constraint was clear (see Table 5.2, Chapter Five). In comparison, the Classification Based on Association rules (CBA) and conditional inference trees may better aid in identifying non-linear patterns as the visualisations illustrate how multiple constraints interact together. Location was shown to be the most influential constraint in AF goal kicking, however other factors such as kick type and pressure also interacted with kick location to influence performance (Chapter Five). The logistic regression model had the highest mean model accuracy in determining goal-kicking effectiveness, however the CBA and conditional inference trees models may be more easily implemented in the applied setting due to their visualisations leading to increased interpretability. These visualisations may allow an improved ability to digest how multiple constraints interact together to influence shot outcome. Furthermore, the visualisation of data may improve analysis and decision-making (Tory & Moller, 2004). In comparison, numerical tables require increased cognitive load to comprehend them (Kale et al., 2018). A balance between model interpretability and accuracy needs to be met in order to translate research to the applied setting.

The balance between interpretability and accuracy in modelling differs based on the aims of coaches and researchers. A model where information is readily accessible may be more important for a coach than an alternative model which is slightly more accurate. Conversely, a researcher may prefer a more specific and sensitive model to more accurately define what is occurring. Therefore, in the transfer of research to the applied setting, these differences need to be considered. Thus, to improve the accessibility and implementation of critical information from data analysis, visualisations should be selected depending on the situation and user.

Visualisations are an essential tool to enable the understanding and appreciation of complex and multidimensional constraints in a system. The ability to visualise multiple variables may further enhance the communication of complex information. For instance, five dimensions can be displayed and manipulated through the two regular axes as well as hue, shape and size of data points. The impact of visualisations on stakeholder decision-making has been examined across forecasting, communication and planning (Fagerlin et al., 2011; Fernandes et al., 2018; Padilla, Creem-Regehr, et al., 2019; Padilla et al., 2017). Furthermore, visualisation aesthetics have been linked with an individual's engagement, enjoyment and memorability (Cawthon & Moere, 2007; Fagerlin et al., 2005; Hullman et al., 2018; Pinker, 1990). Furthermore, stakeholders will have individual preferences, therefore, the ability to create individualised or specific outputs may help improve the implementation of complex analysis in sport.

Fortunately, many machine learning techniques allow for variability with respect to how the findings can be presented or visualised. Thus, versatility in the way sport science can be communicated, visualised and expressed across different formats may increase the likelihood of implementation, ease of interpretation and creation of value within the organisation (Robertson, 2020).

When implementing an RLD to training, a comprehensive understanding of the competition environment is required, as ultimately that is the environment that training is attempting to mimic (McCosker et al., 2019; Pinder, Headrick, & Oudejans, 2015). Understanding competition and training environments together is important when trying to design a training environment which is representative. For example, the knowledge of the number of disposals or the prevalence of certain constraints in competition settings is required to then ensure these are targeted and achieved in training (Ireland et al., 2019). Research has explored the manipulation of constraints and training drills in team sports, such as how the manipulation of playing numbers, number inequalities and field dimensions alter physiological and technical demands (Coito et al., 2019; Klusemann et al., 2012). However, little research has compared the competition environment alongside the training environment (Dawson et al., 2004a; Ireland et al., 2019; Travassos et al., 2012), and how learning from representative environments transfer into competition (Seifert et al., 2019). The methods explored in this thesis aimed to give a better understanding of the competition setting by exploring match events to help design training (Chapter Six). Using association rules, Chapter Six presented methodologies that aimed to understand the degree of representativeness of training tasks. Chapter Six explored the prevalence and impact of constraints on skilled performance in competition and different training modalities. By quantifying the variance in the groupings of constraints, it was found that match simulations were more similar to competition than SSGs. The differences between the training modalities and constraints were not uniform and had varying levels of influence on skilled performance. Findings from Chapter Six could help aid the implementation of a periodised training program, by offering a methodology to measure the manipulation of constraints to make drills harder or easier, such as increasing or decreasing the drill size to alter the level of difficulty (Farrow & Robertson, 2017; Otte et al., 2019). Periodisation is where systematic variations to training design are implemented across short- and long-term time periods with the aim of improving performance (Kiely, 2012). Thus, the methods from Chapter Six offer a tool to measure the influence of implementing a periodised approach to skill training across both training and competition settings.

Sport is continuous in nature. Whilst insights can be gained by analysing match events in isolation, in reality, match events occur in sequence, where each event is dependent on the event before. Chapter Six further developed methodologies from prior chapters to explore the sequential nature of AF. For example, in AF, a handball made under physical pressure with a short time in possession occurs under different circumstances to a handball with no physical pressure or time constraints, and the difference between these was shown to subsequently influence the following disposal. Markov chain models have been used in AF to consider sequential dependencies (Meyer et al., 2006), however the modelling was conducted on probabilities as opposed to the discrete inputs which were used in Chapter Six. The methodologies and analysis techniques to consider the sequential nature of sport are available from research, but are not yet readily implemented. If the sequential nature of sport were considered, it could improve insights offered by analysis. For instance, a study in Rugby League measured the expected point values (EPV) at each stage of play, where each play was measured in isolation (Kempton et al., 2016). Whilst this gave the expected points from each stage of play, if the preceding play was included in the analysis it may have more accurately predict the likely outcome. This could better aid coaches and players in objectively informing tactical decision-making. For instance, it may be found that if a play is on the 30 m line and the preceding play gained more than 20 m then it is best to play quickly as the defence may be out of position. In comparison, if the preceding play gained 5 m, a slower, more systematic, approach may have benefits against a set defence. Thus, the application of methodologies which can account for the sequential and complex nature of sport are critical to give a holistic view of the play. Importantly, these methodological improvements can be applied not only in the skill acquisition and performance analysis disciplines but to other sport science disciplines.

This thesis has outlined an interdisciplinary approach to sports performance research through the lens of ecological dynamics. Focusing on the fields of performance analysis, skill acquisition and data analytics, this thesis has attempted to aid the development and implementation of methodologies to better understand the influence of constraints on skilled performance. Furthermore, this thesis has shown that constraints interact with one another to influence skill performance in AF. The interaction and influence of these constraints differ between competition tiers and occur with different prevalence and impact in competition and training environments. The way findings are visualised may influence their level of implementation in the applied setting, therefore visualisation should be selected depending on the situation and the user. Furthermore, methodologies should attempt to account for the sequential and complex nature of sport to fully capture the coupled interaction between individuals and the environment.

7.2 Industry Implementation

The Australian Football League (AFL) is a multi-billion-dollar sporting organisation. To maintain equality in the competition, the AFL heavily regulates club spending, including salary caps for players and football departments (Gray & Jenkins, 2010). Furthermore, regulations exist on funding and also the number of days athletes are allowed to train with their respective clubs, and as such, resources and time are finite. Therefore, clubs can gain a competitive advantage through innovation in sports science (Buttfield & Polglaze, 2016; Giblin et al., 2016). Applying an interdisciplinary approach alongside advancements in performance analysis is a way to innovate within these limitations to improve performance of individuals and teams. The restrictions faced in AF differ to other sports around the world, but the need for efficient methods to better understand performance exist across all sports.

An interdisciplinary approach within sport science teams can encourage consistency and innovation between departments (Balagué et al., 2017; Glazier, 2017; Rothwell et al., 2020). This can be achieved through a unifying theoretical framework, such as ecological dynamics, which may have major benefits for consistency surrounding data collection, aiding the efficacy of applying findings and promoting a more holistic approach between disciplines (Balagué et al., 2017; Glazier, 2017). Furthermore, a common language that can be used between disciplines such as biomechanics, physiology and performance analysis could accelerate the implementation of findings in the applied setting (Balagué et al., 2017; Rothwell et al., 2020). This concept of a unified language moves beyond written and spoken communication, to include a common way to collect and visualise data. A standard visualisation practice is a critical component for the uptake and use of information, as when presented in a consistent way it may help convey key themes in the data to a large audience (Kale et al., 2018; Larkin & Simon, 1987; Vanderplas, Cook, & Hofmann, 2020). The current standard practice of data collection currently differs between sport science disciplines, resulting in differing methods of data collection, duplicated datasets and the use of additional resources (Couceiro et al., 2016; Glazier, 2017). However, if sports science teams work collectively and spend less time collecting, collating and analysing information in silos, they could group and apply those resources towards the development of research questions, applied practices and innovation. For example, sharing the analysis of how individuals cope under certain constraints within different training modalities between high performance staff and skills/development coaches could help create individualised training plans to aid the development of physiological and technical skills symbiotically, as opposed to two separate plans seeking to achieve separate aims. This interdisciplinary approach could enable sports science to continue to be innovative by applying learnings borrowed from other disciplines.

An interdisciplinary approach to analysis can benefit many disciplines. This thesis demonstrated the utility of a single analytical technique across numerous multiple disciplines and their applied problems. For instance, the rule-based approach used in Chapter Four could inform decision-making across multiple facets of industry, including coaching, list management, recruiting, and high-performance staff. The interaction of constraints identified in this thesis, including time in possession, kick distance and pressure, may help inform a coach of the context in which kicks are occurring. The findings from Chapter Four could help a coach understand the competition environment, and based on the principle of representative design, manipulate training design to replicate these demands (Pinder et al., 2011; Seifert et al., 2019). List management and recruiting could use the same data to identify potential talent and enhance understanding about athletic skill development. For example, a benchmark could be created to define elite performance under various constraints. This concept could be developed to monitor the way an athlete performs and progresses relative to their age group and competition tier. For high-performance, the inclusion of skilled events with physical distance travelled could provide a more complete measure of physical load and therefore better inform decisions around the management of athlete training loads (R. D. Johnston, Black, Harrison, Murray, & Austin, 2018; Sullivan et al., 2014a). Measuring kick distance, velocity and pressure experienced alongside distance travelled can provide a more holistic measurement of accumulated player load, in contrast to solely measuring distance travelled. In current practice, disciplines operate as silos, however an interdisciplinary approach could encourage datasets to be analysed and applied across multiple sport science disciplines (Couceiro et al., 2016; Glazier, 2010; Rothwell et al., 2020).

Chapter Five and Chapter Six further reflect how the findings in this thesis may have impact in the applied setting. Chapter Five demonstrates the value of analysing a single dataset with multiple techniques to understand the benefits and limitations of each, not only in regard to the accuracy of the models, but their ability to be visualised and implemented in the applied setting. Thus, the consideration of user experience is an important aspect of reporting results. In the same manner as the Chapter Four findings, understanding how constraint interaction influences successful goal kicking can inform training design and recruitment (Chapter Five). However, potentially more impactful for training design, are the methodologies presented in Chapter Six. An important aspect of implementing RLD is to firstly understand the competition environment. Chapter Six offers a method to analyse the influence of multiple constraints on kick and handball effectiveness, but also explores the impact of preceding disposals. When the sequential nature of sport is considered it can improve insights offered by analysis by providing more context. This can be implemented by performance analysts, skill acquisition specialists and coaches to assess the impact and prevalence of the appropriate constraints in the training environment, but also to measure the impact of manipulating constraints in the training setting and objectively determine performance.

The practical applications of this thesis are subject to the nature of the sports industry. Thus, parsimony is a critical concept for the applied setting, due to the limitations in resources and time. In competition settings, an infinite number of constraints exist and exert some level of influence (Chapter Three). These include athlete mindset, opposition influence and the development of the game, as highlighted in Chapter Three. To measure all of these constraints is presently an intractable task (Davids & Araújo, 2010). Thus, a level of parsimony needs to be found between collecting enough data on constraints to inform the analysis, without collecting additional information that does not substantially influence the analysis (Robertson & Joyce, 2019; Schelling & Robertson, 2020). For instance, if the collection of five constraints can provide enough insight to aid practitioner decision-making, and the collection of additional three constraints only minimally enhances the insight provided, the applied benefit does not outweigh the additional resources and time required to collect data on the extra three constraints. Therefore, within industry settings the model using five constraints is satisfactory and a better use of resources. Accordingly, it is imperative to identify the most influential constraints to individual and team performance (McCosker et al., 2019; Robertson & Joyce, 2019). Various factors make the implementation of such research innovations difficult.

Due to the nature of the sports industry, implementing research innovations can be difficult and has ethical implications. From an ethical standpoint, it can be difficult to gain informed consent as athletes may feel coerced to participate or may agree to maintain their position in the team. There is a small margin of error in the elite sport setting for implementing large-scale innovations. This is due to the high stakes placed on a win or loss for a club. Poor performance has the potential to impact job security for coaches and athletes. As an example, if a training intervention is unsuccessful or leads to poor performance, a coach or athlete may be replaced in their role. As such, changes to current practices are often met with scepticism (Alamar, 2013). This may be a result of the ingrained nature within professional sport, where implementing alternative or un-tried methods may been seen as too risky or unwise (Brackley et al., 2020). However, subjective analysis based on human expertise is rarely more accurate than long term objective analysis and is also subject to practitioner bias (Martin, Quinn, Ruger, & Kim, 2004; Painczyk et al., 2017). Thus, to make changes to current practice and bridge the divide between research and industry, sport scientists need to present findings in an easily digestible format to aid the uptake of information in the applied setting (see Chapters Three and Five).

As is the case in many disciplines, there is often a knowledge gap between sports science in research and industry. This thesis has suggested methods to improve the implementation of ecological dynamics in research and the applied setting. In sports science research, there are often insufficient practical applications of findings, and conversely in industry there is a lack of awareness or access to academic research (Fullagar, Harper, et al., 2019). There have been some attempts to translate and apply research into practice, however this needs to be furthered.

This could include stakeholder development and education, moreover, making journal subscriptions more available in industry, incorporating a practical application section in journals, increasing the use of infographics, and creating industry partnerships between sporting organisations and universities. It is also important that multivariate analysis is taking place in industry and not just the research setting. Therefore, the upskilling of industry personnel to make multivariate analysis more feasible within industry is critical. This requires improved education, technology and more data than is currently available to account for the complexity of sport. Numerous factors exist in industry which make implementing research innovations difficult, therefore new approaches must be used to help transfer research to industry. Additionally, the language of research has historically been a barrier to translating theoretical concepts into practice, and includes the implementation of ecological dynamics in industry (Chow et al., 2007). The use of common and accessible language could aid the implementation of research in industry (Glazier, 2017). Addressing these issues may aid the further development of critical thinking and new sources of information leading to innovation in research and industry.

7.3 Future Directions

This thesis has offered multiple avenues for future research. Enhancements in sports technology are leading to an increase in quantity and quality of data available. The application of this data in research settings could enhance the measurement of constraints and future metrics. This thesis used notational analysis to measure pressure, however future research could apply improved data which describes player orientation, defensive players location, match context and individual resilience levels to determine objective levels of perceived pressure at a specific time point as well as throughout the entire game (Andrienko et al., 2017; Goldman & Rao, 2012; Pocock et al., 2018; Taki & Hasegawa, 2000). Technology is making continuous data more accessible. Continuous data has the advantage of enabling the user to select appropriate discretisation when required based on the data available and the question being answered, allowing for more user flexibility. The goal kicking analysis in Chapter Five could have created a model which could provide more specific insight based on kick location with continuous data, as opposed to grouping the data in 10 x 10 m or 10 x 20 m bins. However, caution is also required as the improper discretisation of continuous data can impact model accuracy (Bennette & Vickers, 2012; Carey et al., 2018). The use of technology to collect data types such as spatiotemporal, brain activity and emotion tracking could be applied to improve the measurement of constraints both at a specific point and across time. This could additionally lead to the measurement of more constraint variables which may enable more complex models to be designed. This could allow for more representative models to be generated compared with the simple model proposed in Chapter Six. These improvements to data could allow for models to be generated on an individual and team level, offering more impactful insights which may aid the transfer of research into the applied field.

The benefits of ecological dynamics are outlined above, however, the implementation of the framework in industry has had minimal evaluation. Currently knowledge surrounding the efficacy of transferring learning from training interventions to competition is limited (Seifert et al., 2019; Seifert et al., 2016). To create buy-in from stakeholders, interventions such as RLD must have evidence to support their efficacy in an applied setting. Thus, future research needs to quantify the level of transfer of learning from training to competition achieved with by RLD or a CLA approach. Chapter Six discusses the benefits of an RLD, however the ideal frequency and use of representative training has not yet been determined. It also raises the question of whether all training should be representative of the competition environment, or conversely if skills training should be periodised around the representation of the competition environment. Some of the literature has suggested periodisation should occur (Farrow & Robertson, 2017; Otte et al., 2019). A periodised approach to skill acquisition could allow for the acute and longitudinal measurement of interventions in a systematic and holistic manner (Farrow & Robertson, 2017). Future research is required to understand the effect of a periodised approach to skill acquisition, and to compare the benefits and differences to representative training. Furthermore, where transfer does occur, the origin or cause of transfer is unknown (Broadbent, Causer, Williams, & Ford, 2015; Gabbett, Jenkins, & Abernethy, 2009). Learning is very complex and is further complicated by an individual's upbringing, the organisational culture, coaching styles and pedagogies which should be accounted for in future research (Cassidy, Jones, & Potrac, 2008; Occhino, Mallett, Rynne, & Carlisle, 2014; Uehara et al., 2019). Further research is also required to understand differences in individuals, learning capabilities and feedback styles to help account for how these factors also influence the transfer of learning (Broadbent et al., 2015; Wulf, Chiviacowsky, Schiller, & Ávila, 2010; Wulf & Lewthwaite, 2016). It should also be acknowledged that determining whether training implementations are considered successful or not is complicated and can take an extended period of time, which is not always feasible in industry.

Ecological dynamics research has been predominantly conceptual and theoretical in nature. To progress from a mainly theoretical field into the applied setting requires a level of investment and understanding from coaches and other key stakeholders. Future research could apply mixed method approaches to understand how key stakeholders view and apply these areas to best combine experimental and experiential learning (Brackley et al., 2020; Rothwell et al., 2020; Woods, McKeown, Rothwell, et al., 2020). The involvement of key stakeholders and understanding of problems from an industry perspective could help align research questions with the applied setting. To further this, future research should aim to identify the most influential constraints on performance (McCosker et al., 2019). The identification of important constraints could be streamlined through the use of experiential knowledge and can help to better understand the competition and training environments.

Sport science has the ability to learn from other fields and disciplines. As shown in Chapter Three, fields such as technology, analytics and perceptual sciences can aid the uptake and application of sport science and help develop interdisciplinarity in research. To understand how these fields interact with a theoretical framework, such as ecological dynamics, further research is required. Moreover, future research could aim to explore other theoretical frameworks and more fields. Fields such as psychology and education may help practitioners to begin to understand biases, sociology and principles of learning. This could help improve the applicability of future research and could shift the focus on athlete learning and improving training design. The incorporation of fields external to sport science could also help lead to an interdisciplinary approach being implemented in sport science research. The methodologies applied within this thesis have been demonstrated in AF, however the benefits of these methodological considerations are yet to be explored fully in other invasion sports.

7.4 Conclusions

The specific conclusions of this thesis are:

(i) The application of machine learning techniques can be used to enhance performance analysis methodologies in AF.

(ii) The fields of technology, analytics and perceptual sciences could aid the implementation of an interdisciplinary approach in sports science.

(iii) Multivariate analysis techniques (i.e., rule-based approaches) can be applied to measure the interaction and influence of constraints on skilled events. The interaction and influence of constraints on field kicking performance was found to differ between competition tiers.

(iv) Field location was shown to be the most influential constraint in AF goal kicking. However, other factors, such as kick type and pressure, interacted with location to influence performance.

(v) Differences in analysis outputs were identified. Feasibility and interpretability were highlighted as important factors to implement research in the applied setting.

(vi) Major differences existed in the prevalence and frequency of constraints between training and competition in the data used in this study. Match simulations were more closely aligned with competition matches than SSGs.

(vii) The outcome of a disposal in AF was not only influenced by the constraints acting upon that disposal, but was also impacted by the sequence of disposals and the constraints of preceding disposals.

(viii) Future work could focus on the development of methodologies which account for the complex nature of sport. Sports performance research should move beyond recording discrete events to analysing continuous events to provide a more accurate representation of the complex system of sport.

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APPENDICES

APPENDIX A – APPROVAL TO CONDUCT RESEARCH

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

Quest Ethics Notification - Application Process Finalised - Application Approved

quest.noreply@vu.edu.au <quest.noreply@vu.edu.au>
Sam Robertson; Peter Ronald Browne; Alice.Sweeting@vu.edu.au; S.Morgan@latrobe.edu.au
Monday, 28 May 2018 at 3:03 pm
Show Details

Dear ASPR SAMUEL ROBERTSON,

Your ethics application has been formally reviewed and finalised.

» Application ID: HRE18-022
» Chief Investigator: ASPR SAMUEL ROBERTSON
» Other Investigators: MR Peter Browne, DR STUART MORGAN, MISS ALICE SWEETING
» Application Title: Development of an Expected Goals model in 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; 28/05/2018.

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

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