A CONSTRAINTS-LED APPROACH TO INFORMING TEAM SPORT TRAINING DESIGN

Ben Teune

B. Sp & Ex Sci, B. Sci (Hons)

This thesis is submitted for the fulfilment of the requirements for the award of

DOCTORATE OF PHILOSOPHY

Institute for Health and Sport

Victoria University

Aug 2022

ABSTRACT

The design of practice environments supportive of learning and performance is a contemporary challenge for practitioners in high performance sport. To address such a challenge, the coupling of contemporary pedagogical frameworks, such as the constraints-led approach, with the practical implementation of tools from sports analytics may be beneficial. This thesis explored the measurement and analysis of key task, environmental and individual constraints to guide practice design in professional Australian Football. Across five studies, various analytical techniques were used to evaluate different constraints and their interactions, and determine their effect on athlete and team behaviour. Spatiotemporal player tracking data was first analysed to determine a novel, continuous measure for the constraint of pressure and its influence on performance. Rule association and regression trees were applied to evaluate the influence of environmental, task and individual constraint interactions on athlete skilled behaviour. Univariate and multivariate change point analyses were applied to inform the duration of training activities to support skill learning. Rule association and classification trees were used to evaluate the influence of a numerical constraint manipulation on interacting technical, tactical, and physical team behaviours. Collectively, the findings from these studies not only assist practitioners in the design of practice tasks but show how constraint manipulations may challenge or promote various behaviours in team sports athletes. Moreover, this thesis demonstrates the utility of multivariate analytical techniques in the exploration of constraints interaction in sport. The suitability of such techniques for the measurement of complex and non-linear interactions between athletes, the task and environment, was highlighted. Practitioners can integrate and adapt these analytical tools, in conjunction with the constraints-led approach, to inform the design of practice tasks that facilitate learning and development in high performance sport.

STUDENTS DECLARATION

Doctor of Philosophy

"I, Ben Teune declare that the PhD thesis entitled

A constraints-led approach to informing team sport training design

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".

"I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures."

"All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee HRE20-138."

Signed: [redacted] Date: 15/08/2022

Name: Ben Teune

ID Number: s462207

DETAILS OF INCLUDED PAPERS: THESIS WITH PUBLICATION

Please list details of each scholarly publication and/or manuscript included in the thesis submission. Copies of published scholarly publications and/or manuscripts submitted and/or final draft manuscripts should also be included in the thesis submission.

This table must be incorporated in the thesis before the Table of Contents.

Chapter No.	Publication Title	Publication Status • Published • Accepted for publication • In revised and resubmit stage • Under review • Manuscript ready for submission	Publication Details • Citation, if published • Title, Journal, Date of acceptance letter and Corresponding editor's email address • Title, Journal, Date of submission
3	Application of a continuous pressure metric for Australian Football	Published	Teune, B., Spencer, B., Sweeting., A., Woods, C., Inness, M., Robertson, S. (2021) Application of a continuous pressure metric for Australian football. Journal of Sport Science. 39(13): 1548-1554
4	The influence of environmental and task constraint interaction on skilled behaviour in Australian Football	Published	Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2021) The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. European. Journal of Sport Science. 0(0): 1-8
5	The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training	Published	Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2022) The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training. Journal of Sport Science. 40(17): 1991-1999
6	A method to inform team sport training activity duration with change point analysis	Published	Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2022) A method to inform team sport training activity duration with change point analysis. PLOS ONE. 17(3): e0265848
7	Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour	Published	Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2022) Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour. PLOS ONE. 17 (12): e0278844

Declaration by [candidate name]: Ben Teune

Signature: Ben Teune Digitally signed by Ben Teune Date: 2022.11.30 11:57:53 +11'00'

Date: 30/11/2022

ACKNOWLEDGEMENTS

Although my name is on the front, this thesis would not be at all possible without the help and guidance of many extremely influential people.

First and foremost, to my principal supervisor, Professor Sam Robertson. Your expertise and insight has been invaluable and I consider myself fortunate to be witness to your work ethic and innovation. As one of the leaders in our field, I'll always be grateful that you took a chance on me, accepting me as a student before we had even met and while I lived on the other side of the country. Likewise, to my co-supervisory group, Dr. Alice Sweeting, Dr. Carl Woods and Dr. Mathew Inness. I've been really lucky to have supervisors with such diverse skill sets and backgrounds. To Alice - thank you for always putting up with my R questions, lending your coding expertise, and punishing my grammatical errors right to the very end. To Carl – it was a massive win for me when you decided to move to VU. I'm always in awe of your writing and the way you communicate your ideas. Your philosophical insights have challenged me consistently throughout my candidature. Finally, to Mat - thanks for all your input and support in club-land. It was a massive confidence booster knowing there was someone who had my back down in the footy department. I've also always admired how you conduct your work with humility and generosity which, I think, is extremely under-rated in high performance sport.

It's no secret I've been incredibly interested in the applied side of sport. A PhD in elite sport has been an incredible conduit to explore this. So a massive thank you goes out to the Western Bulldogs and all the staff who made me feel welcome and gave me opportunities to conduct my research and apply my skills. The practical knowledge and experience I have gained during my years here were unreal. The chance to work in the AFL was a bit surreal, and the experience of going to a grand final will be one not quickly forgotten. Some specific appreciation for Jason Smith and Chris Caporaso. One day during a pre-season I just decided to set up shop in your office and I never left. You were both extremely generous with your time and expertise, putting up with me bugging you with questions and supporting my role during some extremely unprecedented seasons.

To all my fellow PhD students at W202. I know these last few years were not kind to most of us, and by the end, very few of us remained. During the early years, when W202 was humming it was a warm and enjoyable place to work and I've really missed seeing everyone since. There are few who can relate to you during a PhD, so you guys were among that minority capable of relieving some academic loneliness.

Doing a PhD has been treacherous, glorious, mind-boggling, frenetic, isolating, freeing and spectacularly overwhelming. To counteract that rollercoaster you need a life outside of it. All my friends and family, who couldn't recite my research topic for all the money in the world, but blindly supported me every step of the way – you didn't go unnoticed. To everyone in Perth, leaving was hard, but you continued to support me despite the distance and the border closures. I feel overwhelmingly blessed to remain close with so many of you. For all the gang in Melbourne, you've been game-changing in helping me feel settled and at home over here. You're a home away from home and a family away from family. For most of you guys, this submission will mark your first moment getting to know non-PhD Ben.

Finally, to the most important contributor there is, my wife Ash. I know leaving your home was one of the hardest things you've had to do and it was only compounded by the global situation of recent times. Despite everything, you have been outstandingly loyal, unwaveringly determined and unrelentingly supportive. Your love has kept me grounded, secure and most importantly, overwhelmingly happy. I'm immensely proud of how we battled through some major ups and downs these last few years. I mean this in all seriousness; finishing this thesis is an equally important testament to your work, as it is mine. I think we're both looking forward to an exciting new chapter and probably most of all, not being a student any more.

PUBLICATIONS ARISING DURING CANDIDATURE

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

1. Teune, B., Spencer, B., Sweeting, A., Woods, C., Inness, M., Robertson, S. (2021) Application of a continuous pressure metric for Australian football. *Journal of Sports Sciences. 39(13): 1548-1554,* doi: 10.1080/02640414.2021.1886416 (Chapter Three)
2. Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2021) The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. *European Journal of Sport Science. 22(8): 1-8,* doi: 10.1080/17461391.2021.1958011 (Chapter Four)
3. Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2022) A method to inform team sport training activity duration with change point analysis. *PLoS ONE. 17(3): e0265848,* doi: 10.1371/journal.pone.0265848 (Chapter Six)
4. Teune. B., Woods, C., Inness, M., Sweeting, A., Robertson, S. (2022) The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training. *Journal of Sports Sciences. 40(17): 1991-1999,* doi: 10.1080/02640414.2022.2124013 (Chapter Five)
5. Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2022) Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour. *PLoS ONE. 17(12): e0278644,* doi: 10.1371/journal.pone.0278644 (Chapter Seven)

PRESENTATIONS ARISING DURING CANDIDATURE

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

1. Teune, B., Woods, C., Sweeting, A., Inness, M., Robertson, S. (2021) The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. Presented at *2021 Australasian Skill Acquisition Network Conference (Findings from work relating to Chapter Four)*

TABLE OF CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

=	equals
<	less than
>	greater than
%	percent
±	plus or minus
n	Number of participants
p	p-value
t	Test statistic
1SD	One Standard Deviation
AF	Australian Football
AFL	Australian Football League
B	Coefficient
CLA	Constraints-led Approach
e.g.	for example
GPS	Global Positioning System
HIR	High Intensity Running
LPS	Local Positioning System
m	Metres
$m \bullet min^{-1}$	Metres per minute
min	Minutes
p/min	per minute
s	Seconds
SD	Standard Deviation
SE	Standard Error

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER ONE – INTRODUCTION

Chapter Overview

This chapter outlines the background and objectives of the thesis and offers an introduction to Australian Football to provide context for the analyses within the proceeding chapters.

1.1 Thesis background and objectives

This thesis aims to contribute to sport practice and literature which may enhance how the constraints-led approach (CLA) is applied in team sport. The studies in this thesis seek to provide sport practitioners with tools which can support evaluations of player behaviour and inform training design. Specifically, data and analytics are utilised to improve constraint measurement and enhance the analysis of constraint interaction. Sport practitioners may adapt these techniques to support their decision making to facilitate athlete skill acquisition during training. The studies within this thesis are conducted in the applied environment of a professional Australian Football (AF) club to improve the practical utility and feasibility of their outcomes for sport practitioners.

Practice is an essential exercise to achieve expertise in a variety of domains, including sport (Ericsson & Smith, 1991; Newell & Rovegno, 1990). While the accumulation of practice time is important to developing skill, the quality of such practice is also suggested as equally important (Davids, 2000). Coaches have expert domain-specific knowledge which informs the structure and design of training (Nash & Collins, 2006), which may be further supported by objective insights gained through research. Current theoretical insights which guide training design could be complemented with investigations of practical tools which may support coaches (Newcombe et al., 2019). This may help bridge the gap between training design theory and application, which exists in high-performance sport (Cushion et al., 2012; Kinnerk et al., 2021; Stone et al., 2021). For example, despite the discussed benefits of small-sided games (Davids et al., 2008, 2013), they can have limited implementation by some team-sport coaches, such as in Gaelic Football (Kinnerk et al., 2021). To support coaches in their implementation of such training tasks, tools which objectively evaluate the dynamic and interactive behaviour of athletes may be beneficial. This could support coaches by informing them of complex relationships between the design of training tasks and the emergent behaviour of their athletes. This information may guide coach decisions on training modifications required to achieve task goals (Correia et al., 2019). To interpret this information appropriately, principles of a skill acquisition framework are necessary to guide how practice may be structured and designed (Woods, McKeown, O'Sullivan, et al., 2020; Woods, McKeown, Rothwell, et al., 2020). One such framework is the CLA (Davids et al., 2008).

The CLA is a framework which may be used by sport practitioners to conceptualise the emergent movement of athletes (Davids et al., 2008). According to the CLA, sport practitioners can manipulate constraints during practice activities to facilitate skill acquisition and enhance sport performance (Chow, 2013; Renshaw & Chow, 2019). By manipulating constraints, coaches may guide or nudge athletes towards new or more useful coordinated movements (Renshaw et al., 2010). The framework of the CLA, therefore, positions coaches as "learning designers", which emphasises constructing and manipulating training environments which can guide an athletes exploration and learning (Woods, McKeown, Rothwell, et al., 2020). Constraints are defined as boundaries to the learners movement system which limit the functional solutions a learner may use to achieve a task (Newell, 1985). Thus, athletes' skilled behaviour cannot be appropriately evaluated without the critical contextual information of constraints (Browne, Sweeting, et al., 2019). Moreover, improved measurements of constraints may support more detailed understanding of athlete behaviour. The interaction between constraints is a key tenet to the CLA and thus, methods which can determine constraint interaction and their influence on skilled behaviour may be beneficial to support training design (Browne et al., 2021).

Within sport, there has been an increased implementation of data and technology (Rein & Memmert, 2016). There is scope to harness technology and analytics, within the framework of the CLA, to provide tools and methods which can support the design of training environments (McCosker et al., 2021; Woods, Araújo, et al., 2021). Technology such as, player tracking systems and visual annotation software, can be harnessed to provide practitioners with information (Gudmundsson & Horton, 2017; Rein & Memmert, 2016). These technologies are capable of collecting a wide range of data on varying sport constructs including events, locations and distances (Glazier, 2010). Application of these technologies previously tended to investigate the output of the individual athlete however, has been expanded to explore the athletes relationship with the environment and collective team behaviours (Browne et al., 2021; McCosker et al., 2021). Accordingly, many key constraints which may be influencing athlete behaviour can be measured. Through analyses of this data, it may be possible to provide deeper insight on how athlete behaviour is being shaped by interacting constraints in training activities (Browne et al., 2021). Improved analytical techniques, such as machine learning, may be applicable to support the implementation of the CLA as they are capable of discovering important relationships between interacting constraints and handling large datasets which are increasingly prevalent in sport (Browne et al., 2021). A further opportunity may be to leverage technology and analytics to improve constraint measurement using continuous data formats (Corbett et al., 2019; Gudmundsson & Horton, 2017; Gudmundsson & Wolle, 2014). The application of technology and analytics, within a skill acquisition framework such as the CLA, may have benefits to support coaches and sport practitioners to inform training design, with specific applications potentially existing in AF.

1.2 Australian Football

AF is an invasion style team sport consisting of 22 players on each team (18 on field and four interchange players) and one ball. As shown in Figure 1.1, AF is played on a large oval shaped field with lengths ranging between 135m-185m and widths ranging between 110m-155m (Australian Football League, 2021b). An AF match is played in four quarters of 20 minutes, plus time during stoppages in play (approximately 10 minutes). A six minute interval is provided at the end of the first and third quarter and a 20 minute interval at half-time. The current regulations allow a maximum of 75 player interchanges to occur at any time during the match (Australian Football League, 2021b).

The aim of AF is to score more points than your opponents by kicking the ball through either the "goal" or "behind" posts. The two centre posts at either end of the field represent each team's "goal" which award six points to the team. The two outer posts at either side of the goalposts represent "behinds" which award one point to the team. Players attempt to maintain possession of the ball and advance it down the field towards the goals to score. Players may pass the ball to

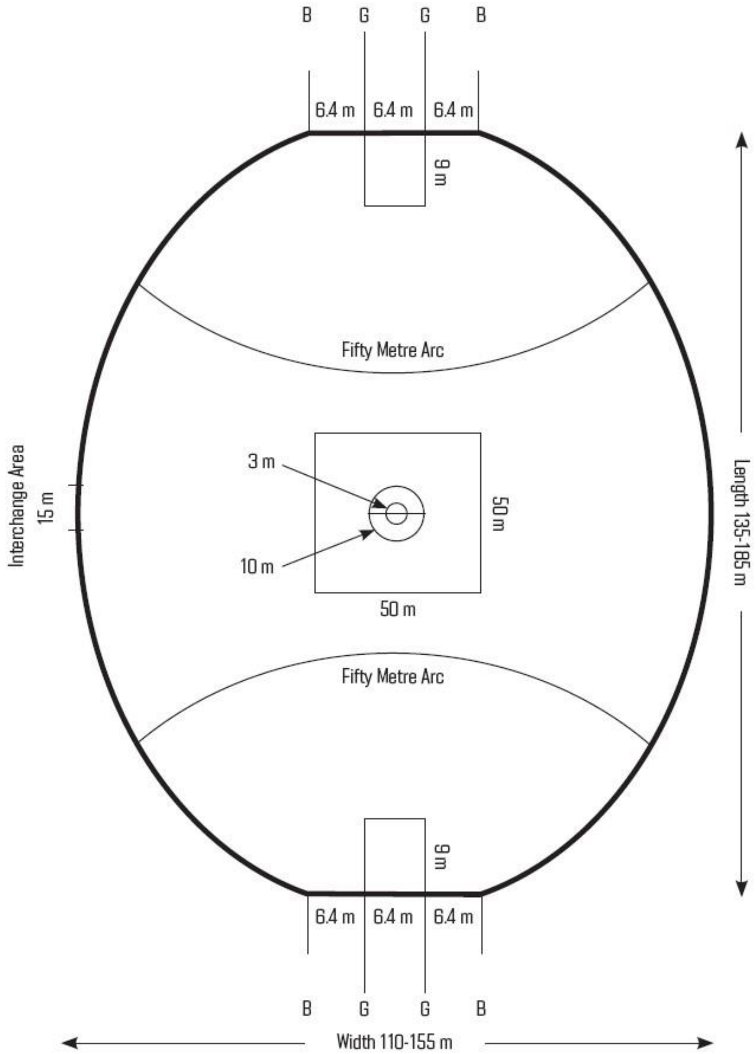


Figure 1.1 Australian Football ground dimensions (Australian Football League, 2021)

one-another through handballing or kicking. When handballing, players are required to punch the ball with a closed fist. Throwing the ball is not permitted. Players are also able to carry the ball indefinitely if the ball is bounced at least once every 15m. Players are generally allocated one of three positions: defender, midfielder or forward. Within this there are various sub-positions such as ruck, wing, half-back or half-forward. However, unlike other sports, such as netball, player positions are dynamic and not restricted to any portion of the field or governed by any specific rules.

To compete in AF, players require high levels of technical skill proficiency and a range of physical qualities including aerobic fitness and agility (A. Gray & Jenkins, 2010; Johnston et al., 2018). During matches players can cover, on average, distances of 12.6 km at speeds of 129 m/min which is higher than other football codes including soccer and rugby league (Varley et al., 2014). Accordingly, to provide athletes with opportunities to develop skills and adapt physically, AF pre-season training can be approximately 17 weeks in length with a typical season of 23 weeks (Moreira et al., 2015). During training sessions, various modalities are utilised including resistance training, aerobic conditioning, games-based activities and closed technical drills (Farrow et al., 2008; Ritchie et al., 2016).

AF is predominantly played in Australia with over 800,000 registered players at all levels of competition (Australian Football League, 2021a). The Australian Football League (AFL) is the single professional AF league which competes at a national level in Australia. A semi-professional national Australian Football League Women's also exists with additional semi-professional state league competitions for both men and women. The AFL is highly regulated including strict "salary-caps" and "soft-caps" which limit the spending of each club on player wages and items relating to performance including staff salaries, equipment, or software. To equalise the recruitment of future talent, each season all clubs are awarded draft picks inversely related to their previous seasons final ladder position. Furthermore, rule changes are implemented regularly which has influenced the evolution of AF game styles (Woods, Robertson, et al., 2017). Thus, sport science literature has grown as teams seek performance benefits within the changing constraints of the league (Johnston et al., 2018). The physical and technical demands of AF competition, alongside the strict regulations on high-performance programs, present AF as a sport which may benefit from enhanced training methods to support athlete development. Thus, this thesis focusses on enhancing the design of practice activities to improve player performance and AF is used as an exemplar sport to demonstrate it's applications.

1.3 Thesis Outline

The primary aim of this thesis is to develop methods for sport practitioners to evaluate skilled behaviour and inform training activity design, exemplified in AF.

Following this introductory chapter, this thesis contains seven further chapters as outlined:

- Chapter One introduces the background and aim of the thesis.
- Chapter Two reviews the relevant literature in AF and other team sports.
- Chapter Three explores how spatiotemporal analysis of player tracking data may be used to measure the constraint of *pressure* on a continuous scale.
- Chapter Four investigates how task and environmental constraints may be analysed together using a machine learning algorithm, association rules. Association rules are applied to evaluate player behaviour within constraint manipulations during AF training activities.
- Chapter Five expands on Chapter Four by investigating how interactions between all constraint classes, individual, task and environmental, may be considered. This is applied during AF training to evaluate and inform activity design.
- Chapter Six explores how continuous time-series analysis may evaluate player behaviour to inform training activity duration. A single AF training activity is used to exemplify this approach in univariate and multivariate formats.
- Chapter Seven investigates how practitioners can evaluate the influence of a single constraint manipulation. Methods are exemplified which simultaneously consider player skilled actions, team coordination and physical running patterns.
- Chapter Eight provides a summary of the preceding chapters and discusses the applications and implications for sport practitioners. It also outlines directions for future work in the area.

CHAPTER TWO – REVIEW OF LITERATURE

Chapter Overview

This chapter outlines the literature pertinent to the research contained in this thesis. The chapter sections overview literature relevant to training, skill acquisition and informing training design.

2.1 Training

It has been well established that sport training, or practice, is an important component to skill development and achieving excellence. Although many factors, such as individual characteristics and environmental features, contribute to achieving excellence, practice is suggested as the most important (Ericsson & Smith, 1991; Howe et al., 1998; Newell & Rovegno, 1990). It has consistently been demonstrated that time spent in practice is associated with greater levels of expertise in a variety of domains such as chess (Charness et al., 2005; Simon & Chase, 1988), music (Ericsson et al., 1993; Krampe, 1994), mathematics (Gustin, 1985) and sport (Baker, Cote, et al., 2003; Helsen et al., 1998; Howe et al., 1998; Starkes et al., 1996; Ward et al., 2007). This notion is consistent with the "10 year rule", where it was originally hypothesised that expertise could only be attained after 10 years of experience in a specific domain (Simon & Chase, 1988). This was further refined with the introduction of the deliberate practice paradigm which placed importance on activities with a specific purpose of increasing performance (Ericsson et al., 1993). Time spent in activities with the purpose of improving skill is thus critical to its development. This relationship was suggested to follow a power law function, where learning would occur rapidly during the beginning stages but the rate of learning would decrease over time (Newell, 1991). To attenuate the diminishing returns of this relationship, a growing research interest focussed on optimising the design and structure of practice activities.

Although it is clear practice quantity is important to gaining expertise it remains debatable as to the micro or macroscopic structures of practice which can most effectively enhance skill development (Janelle & Hillman, 2003; Williams & Hodges, 2005). The effective structure of practice may also be further influenced by the skill level of the learner (Guadagnoli & Lee, 2004; Orth et al., 2018). In sport, contrary to the notion of deliberate practice, the contribution of "play" has also been supported as important in the development of skill and expertise during early stages of learning (Côté, 1999; Côté et al., 2007). Furthermore, experience in other sports or activities can positively contribute to athletic development and expertise in a desired dominant sport (Baker, Cote, et al., 2003; Strafford et al., 2018). Such research suggests that greater insight into the structure and format of practice activities is required to appropriately understand how expertise is influenced by practice. Indeed, the quality of practice should be considered at least as important as the quantity (Davids, 2000). To this end, a range of literature has explored how practice could be arranged to effectively improve the learning of various skills (Hodges & Williams, 2012).

A number of motor learning principles and techniques have been developed and tested to determine how practice can be optimised for skill learning (Davids et al., 2008; Hodges & Williams, 2012). One such example is the contextual interference effect, which involves randomisation in the sequencing of practice conditions. The use of contextual interference has shown more positive relationships to retention and transfer tests, in comparison with “blocked” formats, in perceptual-cognitive skills such as tennis serve anticipation (Broadbent et al., 2015), or motor skills such as baseball pitching control (Tsutsui et al., 2013) or golf putting (Porter & Magill, 2010). Accordingly, implementation of the contextual interference effect during sport practice may enhance the acquisition of skills. This represents one example of how skill acquisition research may improve practice design. However, despite the recognised influence of practice principles to enhance skill acquisition, concepts emerging from skill acquisition in sport have been limited, compared to other areas such as physiology or biomechanics, in both the literature (Abernethy, 1996) and application in the field (Williams & Ford, 2009). More research is needed which applies skill acquisition principles in real world environments.

Discrepancies exists in the skill acquisition literature, compared to other disciplines. This may be due to two predominant reasons. Firstly, the frequent design of experiments which utilise simple and non-transferable skill acquisition tasks has limited their impact. Motor learning experiments were conducted in controlled laboratory scenarios involving simple tasks which may not properly represent applied environments (Wulf & Shea, 2002). Furthermore, although the significance of practice time has been reported (Ericsson et al., 1993), these experiments were often conducted within short time frames which may not provide enough time for skill learning to occur (Wulf & Shea, 2002). Moreover, the systematic implementation of long term skill acquisition plans in sport also remains largely unexplored (Farrow & Robertson, 2017). Secondly, there was a shortcoming of accurate procedures which can evaluate skill learning. While the inclusion of retention or transfer tests have been useful in laboratory-based tasks (Porter & Magill, 2010), the implementation of such methods to evaluate skills performed in dynamic environments, such as sport, have posed a challenge to researchers (Handford et al., 1997). For these reasons, more work is needed to help advance the field of skill acquisition and translate practice design research to practitioners in the field.

An additional reason for the translational gap in skill acquisition literature is the practical limitations and complexity of implementing practice in sport. The role of a coach or instructor is an integral environmental factor which can influence sport expertise (Baker, Horton, et al., 2003; Gould & Mallett, 2020). To facilitate skill development, coaches may utilise techniques including feedback, direct instruction, demonstration, goal setting or questioning (Correia et al., 2019; O'Connor et al., 2022; Otte et al., 2020). Within this, practice is a critical component to the coaching process (Hodges & Franks, 2002). However, planning practice is a complex and multi-faceted task (Kinnerk et al., 2021). Coaches may facilitate skill learning in athletes through the organisation and manipulation of a large number of variables in the sport environment (Nash et al., 2011). Coaches can consider the design of individual activities and tasks which can appropriately challenge their athletes to learn required skills (Otte et al., 2019). This could be simultaneously considered within the structure of a long term periodisation or plan (Farrow & Robertson, 2017). Furthermore, many constraints exist in the practical application of training design, such as the availability of resources or time, which can require adaptation from coaches away from their intended goal (Vickery & Nichol, 2020). Thus, due to these limitations and considerations in practice, skill acquisition literature has lacked practical application in the field (Cushion et al., 2012). Indeed, investigations into the structure of sport practice have shown that coaches prescribe more time on activities which focus on form and technique rather than game-play based activities, despite literature recommendations (Ford et al., 2010; Low et al., 2013; Vickery & Nichol, 2020). It has also been suggested that the structure of practice tended to be shaped by sociocultural constraints, such as tradition and culture, rather than principles tested in the literature (Roca & Ford, 2020; Rothwell et al., 2018, 2022). Accordingly, there is a gap in applied research which can support coaches in their design of training tasks.

2.1.1 Supporting training design

In sport, there may be opportunities to support practitioners to observe and evaluate their athletes to inform training design and facilitate skill development. To improve practice, it is essential that the coach can identify what skills need to be improved in their athletes. This may include which behaviours are functional, and understand the search and exploitation process of the learners (Correia et al., 2019). As these observations occur, they can inform how to facilitate the skill development of learners. Understanding the relationship between practice design and skilled behaviour is critical information, which can inform the design of appropriate learning environments (Renshaw & Chow, 2019). However, the reliability of the coaching eye has been questioned (Roberts et al., 2020). Humans are also limited in the volume of processible information (Robertson & Joyce, 2019). Furthermore, evaluations of movement behaviour are redundant without reference to specifying contextual information, such as constraints, increasing the complexity of the task (Pol et al., 2020). Therefore, practical tools which can objectively evaluate skilled athlete behaviour within the practice environment would be beneficial to support the coaching process and inform training design. Research in this area would also help bridge the gap between theory and practice (Newcombe et al., 2019) however, is currently lacking.

Some tools and frameworks have sought to assist coaches to inform the structure and design of practice. Skill periodisation frameworks have been suggested to guide micro and macro planning and manipulation of skill variables to enhance skill acquisition (Farrow & Robertson, 2017; Otte et al., 2019). Additionally, questionnaires have been proposed to subjectively measure skill acquisition principles to guide the practitioners decisions during training sessions (Krause et al., 2018; Lascu et al., 2021; Renshaw & Chow, 2019). Although useful, these methods remain limited to subjective observations from a coach’s eye within a single session. To this end, objective tools have also been demonstrated, capable of informing training designs which mimic match requirements (Browne et al., 2020; Woods, McKeown, et al., 2019). Other objective analytical techniques have been demonstrated to assist coaches in training activity prescription (Corbett et al., 2018). In this study, activity characteristics were determined, such as running loads and skilled involvements and were grouped using k-means clustering to identify similar activity types. The activities were also compared to match demands through z scores and specificity indexes (Corbett et al., 2018). This study demonstrated three unique analytical methods which could be implemented and flexibly interchanged according to practitioner needs or preferences (Corbett et al., 2018). Together, this body of work presented subjective and objective tools which coaches and sport practitioners may implement to assist the design and prescription of training environments. To expand this work, research may focus on developing tools which inform how practice features can be modified to influence athlete skill.

There is scope for applied sport science research to focus on evaluating training tasks to enhance practice design. Such research may be used to support coaches and facilitate athlete learning by guiding decisions surrounding practice (Bergmann et al., 2021). One way to improve training design is through objective evaluations of athlete behaviour via performance analysis techniques (Rein & Memmert, 2016; Robertson, 2020). Information gained through this sub-discipline of sport may be used to compare training activities to particular training goals (Corbett et al., 2018) or the representativeness of training to competition (Browne et al., 2020; Woods, McKeown, et al., 2019). Accordingly, this information may be utilised to inform how practice tasks could be modified to better achieve these outcomes. The application of such research may be further improved by also leveraging opportunities to conduct investigations of practice design in the field.

The appropriate design of sport science experiments is essential to ensure effective translation to applications in the field (Bishop, 2008). Indeed, the results of studies which compared training design approaches are limited in their generalisability and thus, lack a clear direction for coaches and sport practitioners (Bergmann et al., 2021). Consequently, there has been a call for more focussed research to be conducted within sporting practice landscapes to improve its practical utility (Bergmann et al., 2021; Davids et al., 2006; Newcombe et al., 2019; Renshaw & Gorman, 2015). Traditionally, this has been a challenge for researchers, but given the rise of technology and innovative methods to collect and analyse data in sport, there are more opportunities to achieve this (Newcombe et al., 2019; Rein & Memmert, 2016). Some examples include tracking systems which can automatically quantify player positioning (Torres-Ronda et al., 2022) or wearable sensors to measure limb movements during sport performance (Cust et al., 2021). Such technology may be utilised to measure changes to technical skill executions or team coordination strategies and used to support coaching and practice design. Further, there have been growing calls for researchers to work *with* sports practitioners to design relevant research questions enhancing how findings could be translated into the real world (Cushion et al., 2012; Greenwood et al., 2012; Renshaw & Gorman, 2015; Ross et al., 2018). Likewise, sport programs may benefit from engagement with a skill acquisition specialist to enhance their training efficacy and performance (Williams & Ford, 2009). Thus, research and sport practice can form a mutually beneficial relationship (Newell & Rovegno, 1990). However, it is pertinent that research directed towards enhancing practice design be interpreted with consideration of skill acquisition theory which can guide a practitioner's decision making.

To achieve research which can enhance skill development in sport, theoretical conceptualisations of skill acquisition are necessary to frame queries relating to the structure and design of practice activities. The theoretical underpinnings of skill acquisition research can inform the interpretation of practical insights for sport practitioners (M. O. Sullivan et al., 2021; Woods, McKeown, Rothwell, et al., 2020; Woods, McKeown, O'Sullivan, et al., 2020). For example, a dominant theoretical perspective in cognitive psychology views skill as an acquired "knowledge structure" within the brain (Adams, 1971; R. A. Schmidt, 1975). Accordingly, this conceptualisation would support a form of practice which focusses on rote repetition to build upon this knowledge. Thus, a coach would structure practice to permit a learner to perform many repetitions of a given task until the movement becomes autonomous. Contrastingly, an ecological dynamics rationale views skilled movement as a property of a learner's interactions with the environment (Davids et al., 1994; Handford et al., 1997). Hence, a coach may seek to design practice which guides a learner's attention to key environmental features which can regulate their actions, encouraging exploration rather than repetition (Chow et al., 2011; Renshaw et al., 2010). Thus, coaches should seek to align with a conceptualisation of skill acquisition to guide their practice design. Likewise, more sport research should be aligned with a theoretical perspective to frame the practical implications of the work (Bergmann et al., 2021). .

2.2 Skill Acquisition

Skill acquisition theory relates to concepts accounting for the progression of learning a variety of skills (DeKeyser et al., 2007). Skill acquisition has spanned a variety of domains including psychology, education and movement science and holds important implications for many fields such as physical education and sport. Skill acquisition, or skill learning, refers to relatively permanent changes in behaviour or knowledge and improvements in the capability to perform skills (Magill & Anderson, 2010; Soderstrom & Bjork, 2015). Skill acquisition is distinct from skill performance which refers to the momentary execution of movements resulting in observable behaviour (Soderstrom & Bjork, 2015). Importantly, skill acquisition is not directly measurable but is inferred from observations and evaluations of skilled performance (Magill & Anderson, 2010). Accordingly, tools which can support coaches to achieve this are critical to facilitating skill acquisition. However, such tools should be grounded in a theoretical perspective of skill acquisition to appropriately frame their implications.

2.2.1 Traditional Perspectives

Dominant theories of skill acquisition have adopted perspectives which align with cognitive psychology. In this perspective, the mind is seen as a representational device which stores information used to control movement (Davids et al., 2008). This perspective has been suggested as a metaphor for a computer, favouring internal storage of representations of the world which may be processed and output as motor actions (Handford et al., 1997). Pre-programmed executive functions which exist in the central nervous system are executed to control the musculoskeletal system and create coordinated movement patterns (Keele, 1968; R. A. Schmidt, 1975). Procedural knowledge may be developed over time allowing faster and more accurate retrieval of conditioned actions, similar to if-then statements, where motor programmes are selected according to relevant stimuli (Adams, 1971; Masson, 1990). Thus, the process of skill acquisition involves the enrichment of an internal structure or schema which becomes more detailed through repetition (Araújo et al., 2019).

According to cognitive processing theories of movement control, implications for skill acquisition and practice design are based on the rote repetition of skills in controlled environments. A practitioner may enhance skill acquisition by increasing the transfer of information through modification of practice task difficulty (Guadagnoli & Lee, 2004; Guadagnoli & Lindquist, 2007). Motor learning may also be facilitated by factors such as motivation (L. Schmidt et al., 2012) and an external focus of attention (Abdollahipour et al., 2015), among others. These can strengthen the neural pathways and develop more robust connections between goals and actions (Wulf & Lewthwaite, 2016). Cognitive processing theories encourage the adoption of a single “correct” technique which may be reinforced or modified by coaches and instructors via techniques such as feedback or demonstrations (Adams, 1971; Davids et al., 2008). This perspective of practice views performance errors as noise which should be eliminated (Davids et al., 2008). Such worldviews of motor learning and control have been influential in the literature however, they have received a number of critiques, such as program storage or the computer metaphor, concerning philosophical, theoretical and methodological issues (Davids et al., 1994; Handford et al., 1997; Newell, 1991).

2.2.1.1 Philosophical limitations

From a philosophical perspective, in cognitive theories, the “mind” is conceptualised as a computer system capable of executing tasks. However, the application of such a metaphor to the study of organic matter, such as the brain, has been queried (Handford et al., 1997). In this conceptualisation the mind is constructed without substance and exists outside of the natural laws of the physical world (Handford et al., 1997). Accordingly, a major issue concerns how mental representations can be explained within physical biology. It has been argued that an appropriate theoretical approach for motor control should find agreement between conceptual constructs and a neuroscientific explanation involving physiological and neural processes of the organism (Araujo & Davids, 2011).

The cognitive control of movement requires organisms to perceive an environmental feature, interpret it's meaning, match this to the relevant movement pattern and then execute the motor program (R. A. Schmidt et al., 2018). This traditional conceptualisation of symbolic representations of the world suggests an indirect access to its features. Accordingly, perceptual stimuli is considered ambiguous without the necessary cognitive interpretation to associate it with coordinative actions (Araujo & Davids, 2011). A symbolic representation system, therefore, requires memory or cognition to interpret the meaning of a perceptual stimulus for a relevant context-specific movement pattern to occur. However, symbolic representations have been critiqued as they must require, at some level, direct access to the world if their origin is to be explained (Warren, 2006). Otherwise their justification may result in explanatory regress, where the meaning of a representation is attributed to some other representation (Warren, 2006). Furthermore, given the ambiguity of symbols, a representational system would be unable to detect errors without external assistance (Golonka & Wilson, 2019). For example, learning to read is impossible without an external instructor providing feedback to help the learner discover the arbitrary relationship between letters and sounds (Golonka & Wilson, 2019). Accordingly, a theoretical perspective which appreciates a direct perception of the environment may be advantageous (Gibson, 1979).

2.2.1.2 Theoretical limitations

A predominant theoretical concern with cognitive perspectives is the significant burden imposed upon biological systems to store, retrieve and process internal motor programs. Motor programs, or schemas, must require enough detail to control numerous degrees of freedom (Bernstein, 1984). For example, human beings are composed of many muscles and joints capable of multi-planar movement. These components each represent multiple degrees of freedom which, as more joints are considered, have exponentially increasing combinations of coordinative states (Bernstein, 1984). Hierarchical control, when assigned to the mind, is responsible for executing all actions to individually control the abundance of joint positions to produce multi-joint coordinated movement. This process of control is further challenged in dynamic and temporally constrained environments, such as sport, where speed, flexibility and accuracy of movement solutions is essential (Davids et al., 1994).

In dynamic situations, such as sport, movement systems have demonstrated characteristics of flexibility and degeneracy (Seifert et al., 2014). They are capable of achieving similar movement outcomes, with varying coordination patterns, as a functional adaptation to changes in environmental conditions (Kugler et al., 1982). To account for this in cognitive theories, feedback loops were postulated to update movement patterns in response to constantly changing contextual conditions (Adams, 1971; R. A. Schmidt, 1975). However, such processes would be cognitively demanding, requiring many computations per second (Handford et al., 1997). The speed of these processes to occur within 200-300 milliseconds has been questioned (Davids et al., 1994). Similarly, despite the presence of feedback, cognitive theories are unable to account for the performance of novel coordinative movements (Newell, 1991). New movement patterns should not be able to be performed without an existing representation of the relevant motor program. Accordingly, an alternative conceptualisation of movement execution processes, which can account for the speed and flexibility demonstrated in situations such as sport, may be necessary.

2.2.1.3 Methodological limitations

Methodologically, traditional theories have been primarily supported with lab-based experiments of simple tasks (Wulf & Shea, 2002). However, the results of such experiments may not be representative of more complex tasks performed in dynamic environments such as sport, music or the workplace (Handford et al., 1997; Wulf & Shea, 2002). Some examples include investigations into the influence of contextual interference or the distribution of practice, where simple tasks which are novel to the participant have been utilised such as golf putting (Porter & Magill, 2010), computerised paddle games (Metalis, 1985) or movement timing tasks (Lee & Genovese, 2013). Highly controlled tasks in which a single variable is manipulated lack the dynamic information which is presented in an applied environment where individuals are required to continuously adapt their actions (Brunswik, 1956). Thus, principles which have been derived from such evidence may not apply to the control of movement during sport. Accordingly, there have been calls for the design of studies which are more representative of environmental conditions to enhance their generalisability beyond the laboratory (Araújo et al., 2007; Brunswik, 1956). Due to this, there was a growing need to conduct research within the performance landscape to appropriately determine its application.

The focus of traditional theories of motor control and learning on cognitive processes have resulted in an *organismic asymmetry* in the literature (Davids & Araújo, 2010b; Dunwoody, 2006). This has occurred due to the bias of skill acquisition theories to attribute the control of functional movement to cognitive processes alone. The result is a trend in motor control research which has over-emphasised the importance of the internal processing of the organism and led to a neglect of the environment the organism is situated in. The focus on internal processes has led to a reductionist paradigm in skill acquisition where investigations of skilled behaviour ignore the constraints external to the performer (Davids & Araújo, 2010b). Indeed, psychological sciences have a history of laboratory based experiments in which external variables are rigorously controlled and results are attributed to models of internal processing within participants (Brunswik, 1947; Handford et al., 1997; Wulf & Shea, 2002). The concept of organismic asymmetry has been suggested to also influence sport science and sport psychology research (Davids & Araújo, 2010b). Accordingly, there has been a call for sport science research to consider the interactions between the performer and the environmental context they are situated in (Davids & Araújo, 2010b; Dunwoody, 2006).

An alternative perspective of motor learning and control, which contrasts the organismic asymmetry observed in cognitive theories, is ecological dynamics. Ecological dynamics is a contemporary theory which conceptualises the emergence of functional motor patterns in organisms as a reciprocal and functional relationship between an organism and the environment (Araújo et al., 2006). Such a conceptualisation de-emphasises the storage and retrieval processes in cognitive psychology and promotes a direct perception of the environment to regulate actions

(Davids et al., 1994). Accordingly, this position does not align with internal symbolic representations of knowledge which are enhanced during skill acquisition (Araujo & Davids, 2011; Handford et al., 1997). Instead, skill acquisition is a process of improving the fit of coordinated actions with key regulatory information in the environment (Araujo & Davids, 2011). As learners explore the environment they become increasingly "attuned" to critical perceptual information, enhancing their functional interaction with the dynamic landscape around them (Araujo et al., 2009; Woods & Davids, 2021). The theoretical conceptualisation of ecological dynamics draws primarily from the domains of dynamical systems theory and ecological psychology (Araújo et al., 2006).

2.2.2 Ecological Dynamics

Ecological dynamics has been influenced by concepts within ecological psychology. A critical concept within ecological psychology is that the control of an organism is not attributed to an internal mechanism but is distributed across the organism-environment system (Gibson, 1979). The organism and the environment form a mutual relationship and are continuously regulated with one another. Perception and action are thus, tightly coupled and must be understood together (Bootsma, 1989). To this end, perception is essential for action and vice versa (Gibson, 1979). The notion of direct perception is important, indicating that invariant information perceived by an organism does not require interpretation or representation within the mind, but directly specifies action coordination (Araújo et al., 2006). Accordingly, there is no need for mental representations or symbols in the mind. For example, in sport, a gap between defenders is perceived directly according to its exploitability for passing (Davids & Araújo, 2010a; Fajen et al., 2008). This concept is commonly exemplified with the visual perceptual system however, importantly, it also applies to other perceptual systems, such as haptic or audio senses (Gibson & Carmichael, 1966). Movement control is cyclical and a continuously evolving process whereby, an individual acts on critical information which in turn, reveals further information which may be used to regulate action (Fajen et al., 2008). Via direct perception, the organism forms a deeply intertwined and dynamic system with the environment, which has been conceptualised as a dynamical system (Araújo et al., 2006).

The motor control system, conceptualised as a dynamical system, can form patterns through the organisation of its interrelated components (Kelso, 1995). The structure and organisation of an organism's coordinative control system is influenced by constraints, which are boundaries to the system. Constraints act as limits to the possible coordinative structures (Clark, 1995). Constraints may exist within the organism, the environment or the task which is being performed (Newell, 1986). The interaction between constraints and the organisation of coordinated movement may result in non-linear changes, where small changes in a few constraints may result in large changes to the overall system structure (Balague et al., 2013; Chow et al., 2011; Pol et al., 2020). The dynamical motor control system exhibits self-organising tendencies, where independent components can spontaneously form coordinated patterns within the boundaries of the constraints imposed on the system (Kauffman, 1993; Kelso, 1995). This (re-)organisation of coordinative structures occurs without external instruction or direction. A natural metaphor for the process of self-organisation can be found in the coordinated movement profiles of a flock of birds flying together or a school of fish swimming in a group (Davids et al., 2008). The self-organising tendencies of dynamical systems provide a contrasting conceptualisation to computer processing metaphors seen in traditional theories. In the neurobiological system, motor control was positioned as a challenge for executive processes to handle, given the numerous degrees of freedom required to control and the speed and accuracy demonstrated to achieve tasks (Bernstein, 1984). However, the concept of dynamical systems relieves the burden of control to any hierarchical structure or function and distributes it across the entire system. This alleviates the issue of internal storage capacity required in information-processing theories of motor control (Kugler et al., 1980; Turvey, 1990).

As an individual interacts with their environment, the perceptual landscape is explored, searching for stable solutions to movement problems (Araujo et al., 2009; Handford et al., 1997; Jacobs & Michaels, 2007). The continuously evolving interaction of the organism and the environment allows for flexible and adaptable movement solutions within the presence of a dynamic environment, which commonly characterises sport. Within ecological dynamics, expertise is developed as performers become increasingly sensitive to the relevant information which can appropriately regulate their context specific actions (Seifert et al., 2013). This process leads to deep, intertwined relationships with the environment (Woods, Rudd, Gray, et al., 2021). Accordingly, there is an absence of internal knowledge enrichment or the acquiring of sophisticated representations. Indeed, a helpful ontological distinction of the skill acquisition process within an ecological dynamics rationale is re-phrasing “skill acquisition” to “skill adaptability” (Araujo & Davids, 2011). For practitioners, the design of learning environments, which align with concepts of ecological dynamics, will adhere to distinctly different principles than traditional theories of skill acquisition. Accordingly, to support sport practitioners in understanding and conceptualising skill acquisition, grounded in ecological dynamics, the constraints-led approach (CLA) is a useful framework.

2.2.3 The Constraints-led Approach

The theoretical underpinnings of ecological dynamics guide the principles of the CLA. The CLA is a framework which views the organism as a system, with interacting degrees of freedom which are shaped by constraints, internal and external to the organism (Davids et al., 2008). Within this framework, constraints are emphasised as critical contextual information which are necessary to influence and understand skilled behaviour. It was suggested that the consideration and manipulation of constraints is beneficial for sport practitioners concerned with skill acquisition (Handford et al., 1997). The constraints model has been suggested as applicable for practitioners due to it’s simplicity (Glazier, 2010). The CLA has also been proposed as a grand unifying theory for sport science (Glazier, 2017) and suggested as a useful framework to promote interdisciplinary collaboration in the sport sciences (Browne et al., 2021; Glazier, 2017). Accordingly, the principles of CLA have important implications for understanding and enhancing sport practice.

Newell (1986) first conceptualised a model of constraints as a framework to understand contextual factors which influence the emergence of coordinated movement. Constraints refer to boundaries or limitations to a movement system (Newell, 1986). Accordingly, the self-organisational properties of the system facilitate the emergence of functional coordinative patterns which satisfy the constraints on their system according to task goals (Davids et al., 2008). According to Newell's (1986) model, constraints were categorised into three groups; organismic, environmental and task (Fig 2.1). The interaction of these constraints reveals a landscape in which states of attraction exist drawing the system to stable organisational solutions (Warren, 2006). Thus, constraints not only provide limits but can accentuate or encourage certain coordinative patterns of movement.

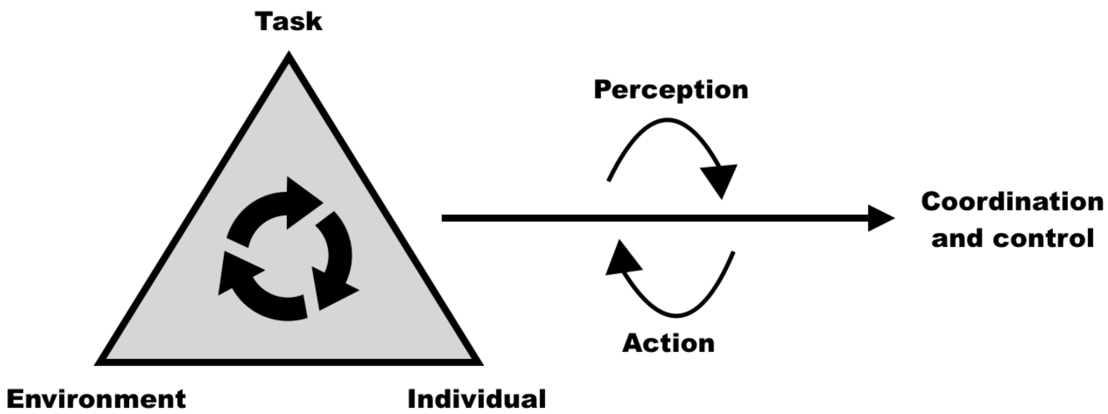


Figure 2.1 An adaptation of Newell's model of interacting constraints (Newell, 1986)

Newell's (1986) model of constraints formed the basis of the CLA (Davids, Araújo, et al., 2003; Davids et al., 2008). The CLA highlights how constraints can be manipulated by coaches and sport practitioners to shape the coordinative tendencies of learner's and improve skill acquisition (Renshaw et al., 2010; Renshaw & Chow, 2019) . Further, the CLA advocates for the mutual relationship between the performer and the environment, appreciating that actions and movements cannot be fully understood without references to the constraints which influence them (Davids & Araújo, 2010b). Accordingly, in sport practice, evaluating athlete skilled behaviour relative to contextual constraint information is pertinent to enhancing skill development. The information gained from skilled action evaluations could inform how practitioners can manipulate key constraints to facilitate a skill acquisition (Timmerman et al., 2019). Indeed, the CLA encourages discovery learning, where constraints can be used to guide the search of learners to discover movement solutions (Davids, Araújo, et al., 2003).

Within the CLA, constraints have varying characteristics which should be considered during implementation in sport practice. Constraints exist at many levels of analysis and may be time dependant or independent (Newell, 1986; Newell et al., 2001). Constraints may be structural, in that they change very little over time, or functional, which change frequently, over varying time-scales including seconds, hours, weeks or years (Balagué et al., 2019; Newell, 1986). Thus, constraints are continuously evolving, such that movement properties are emergent and not pre-determined at some particular time (Araújo et al., 2006). Additionally, constraints exist at different levels and interact between levels (Balagué et al., 2019; Pol et al., 2020). Accordingly, constraints can be viewed as "nested" where interactions may occur bi-directionally through time scales and levels (Balagué et al., 2019). For example, in sport, constraints which act upon an entire team, such as tactics or current score, will constraint an individuals' action also. Likewise, slow changing socio-cultural constraints, such as values and philosophies of a club's organisation, may influence the actions and structure of the team, including their tactics or recruitment strategies (Rothwell et al., 2018). Accordingly, the CLA implies a multi-levelled and multi-time scaled approach to athlete development occurring over micro (sessions/weeks) and macro (months/years) time scales (M. O. Sullivan et al., 2021). Indeed, constraints influence has been demonstrated at multiple scales of analysis such as individual kinematics (Chow et al., 2007, 2008), attacker-defender dyadic relationships (Cordovil et al., 2009; Passos et al., 2012), team and opposition positional interaction (Alexander, Spencer, Sweeting, et al., 2019; Bourbousson et al., 2014; Silva, Duarte, et al., 2014) or geographic and socio-cultural levels (Roca & Ford, 2020; Rothwell et al., 2018, 2022). Thus, the complex interaction of constraints within sport may be a challenge to the practical implementation of the CLA. This presents an important area of opportunity to provide support.

2.2.3.1 Individual Constraints

Individual constraints refer to constraints which exist internal to the action performer (Newell, 1986). In the literature these are also referred to as organismic or performer constraints (Davids et al., 2008; Renshaw et al., 2010). Individual constraints may be structural or functional. Structural individual constraints remain relatively time independent, in that they are consistent over large time scales, indicative of the general rate of change. Examples of structural constraints are age (Almeida et al., 2016), height (Cordovil et al., 2009) or skill level (Silva, Duarte, et al., 2014; Silva, Travassos, et al., 2014). Alternatively, functional individual constraints tend to have fast rates of change and are relatively time dependent. Such examples include emotions (Headrick et al., 2015), fatigue (Lyons et al., 2006) or previous performance (Pocock et al., 2018). Individual constraints are unique to each organism and may also include an organism's intentions (Davids et al., 2008). A learner's intentions relate to their perceived task goals and may be considered central in shaping the search and selection of affordances (Renshaw & Chow, 2019). Further, individual constraints will emerge and decay throughout the learning process (Renshaw et al., 2010). Given the influence of individual constraints, there can be no universal optimal movement solutions for any given task (Glazier & Davids, 2009). Individuals may self-organise to different, yet each appropriate, coordinated movement patterns. Similarly, through practice over time, individuals display unique progressions of technique development (Chow et al., 2008). In sport, it is clear that individual constraints shape the actions of performers, guiding their attention towards movement solutions.

2.2.3.2 Environmental constraints

According to Newell's (1986) model, environmental constraints can be considered as any constraint which exists external to the performer. Although this definition has been regarded as ambiguous (Newell & Jordan, 2007), environmental constraints are generally considered as those not manipulated by practitioners (Renshaw et al., 2010; Renshaw & Chow, 2019). Like individual constraints, environmental constraints may be relatively time dependent or independent.

Constraints such as gravity or light remain consistent over long time-scales however constraints such as wind speed or game score may be relatively fast-changing (Balagué et al., 2019).

Environmental constraints can be further classified into physical and socio-cultural (Renshaw & Chow, 2019). Physical constraints are substantial features of the environment such as gravity, light, weather or surface type (Brito et al., 2017). Alternatively, location, such as indoor gyms or outdoor parks, and competition, such as elite or sub-elite (Woods, Jarvis, et al., 2019), are important environmental constraints. Contrastingly, socio-cultural constraints are intangible and include the values or ethos of an organisation, or the cultural and social expectations of a group. Such environmental constraints are features of the "form of life" which shapes and influences behaviours and values of a community (Rothwell et al., 2018). For example, the industrialist history and tradition of the United Kingdom was suggested to influence autocratic coaching styles which limited the autonomy of player behaviour in Rugby Union (Rothwell et al., 2018). Socio-cultural values can shape the ways players engage with their environment during training sessions (Rothwell et al., 2022). Similarly, the structure, or lack thereof, in practice sessions is influenced by national cultures and values (Uehara et al., 2018; Vaughan et al., 2021).

2.2.3.3 Task Constraints

Task constraints exist external to the performer and relate to aspects of the task being performed (Newell, 1986). These include constraints relating to the goal of the task, the equipment used or the rules which govern the performance (Newell, 1986). Task constraints can be further categorised as instructional or informational. Informational constraints are features in which information may be perceived to regulate motor patterns. For example, in cricket, the presence of a bowler is an informational constraint which batters use to regulate the timing and coordination of strokes (Pinder et al., 2009). Alternatively, instructional constraints exist as rules or directions which may be communicated visually or verbally, such as tactical instructions provided by a coach (Balagué et al., 2019). Task constraints may also be implemented for a specific or non-specific movement outcome (Newell, 1986). A specific constraint would be used to limit the required movement outcome to a particular response. However, non-specific constraints permit room for interpretation and variability in which a performer may exhibit a range of responses (Balagué et al., 2019; Newell, 1986). Instructions and rules may be manipulated by sport practitioners to constrain the skilled movement of their athletes however, are distinct from physical task constraints.

Physical task constraints differ from goals and rules in that they are substantial and tangible (Newell, 1986). Physical constraints may inhibit or encourage a range of motor responses through a range of applications including the modification of equipment (Buszard et al., 2016), addition of wearable loads (Trounson et al., 2020) or the physical restriction of space when performing movements (Verhoeff et al., 2018). For example, in tennis, body scaling the racquets (Fitzpatrick et al., 2018) or the ball and net sizes (Farrow & Reid, 2010) promoted more functional movement solutions and elicited greater stroke learning outcomes. The addition of wearable resistance during running tasks is useful for promoting kinematic variability (Trounson et al., 2020).

Task constraints have been proposed as the most important class of constraints as they can be readily manipulated by practitioners (Renshaw et al., 2010). For example, task goals, equipment or playing area dimensions may be easily modified during practice tasks to promote the emergence of particular skills. Task constraints may be accentuated or dampened to train decision making (Araujo et al., 2009; Davids et al., 2013; Passos et al., 2008), stabilise or perturb current movement solutions (Chow, 2013; Chow et al., 2011; Renshaw et al., 2009) or promote creativity (Orth et al., 2017; Santos et al., 2016; Torrents et al., 2021; Vaughan et al., 2019). Small sided games present effective modalities with which to implement task constraint manipulations whilst still maintaining an imitation of the performance environment (Davids et al., 2013). To effectively leverage task constraint manipulation practitioners should possess adept knowledge about the game to develop athlete’s knowledge in the game (M. O. Sullivan et al., 2021).

Literature has investigated the influence that constraint manipulations may have on physical, skilled and tactical behaviour in various team sports. Typically, these studies are conducted during small side games as commonly seen in the training environment. Task constraints are the most frequently manipulated constraint in literature. Of these, manipulations of the number of players and field dimensions are the most frequently manipulated (Ometto et al., 2018). For example, creating an outnumber for the attacking team increased kicking efficiency in AF (Bonney et al., 2020) and the frequency of correct decision making in soccer (Vaeyens et al., 2007). Additionally, an attacking outnumber increased the mean distance between attackers and defenders during a small side game (Vilar et al., 2014). Decreasing the overall number of players as shown mixed results finding a decrease in the frequency of certain technical actions such as interceptions and passes in soccer (Owen et al., 2011) but an increase in passes (Timmerman et al., 2019) and action success in field hockey (Timmerman et al., 2017). Decreasing the number of players increases the physical demands (Abrantes et al., 2012; Bonney et al., 2020) however, small manipulations of one or two players per side have shown minimal influence in technical actions in soccer (Abrantes et al., 2012) and AF (Bonney et al., 2020).

Field size manipulations are also prevalent in literature across multiple sports. Increases in field size were related to increased physical output but the reduction in certain technical actions such as tackles and turnovers or shots in AF (Fleay et al., 2018) and soccer (Kelly & Drust, 2009). In soccer, length and width manipulations influenced new positioning strategies and interactions between team mates and opposition to suit the demands of the task (Frencken et al., 2013). Increasing field size has also been shown to increase high intensity running demands and perceived intensity (Nunes et al., 2021).

Other task constraint manipulations involve rule modifications or instructional directions. Relative starting positions of attackers and defenders influence action processes and outcomes such as crossing in soccer (Correia et al., 2012; Orth et al., 2014) and a try or tackle in rugby. Manipulations of scoring targets has been shown to influence technical actions in field hockey (Timmerman et al., 2019) and soccer (Almeida et al., 2016; Travassos et al., 2014) where the manipulation of additional targets increases the frequency of shots (Timmerman et al., 2019; Travassos et al., 2014) and elongated the distance between players (Almeida et al., 2016) and the removal of targets increases the frequency of passes (Timmerman et al., 2019). Tactical instructions provided to basketball players, such as a conservative play style, increased the time to move the ball down the court to score (Cordovil et al., 2009). Together, the work investigating task constraint manipulations highlights the influence practitioners may have in shaping the behaviour of their athletes. To build upon this research, there are opportunities to examine how constraints may interact with one another.

2.2.3.4 Constraint Interaction

A key tenet to the CLA, is that constraints do not act in isolation but interact together dynamically and non-linearly (Balagué et al., 2019; Newell, 1985). Organismic movement systems are adaptive, with motor patterns continuously emerging and fitting their structure according to the changes and fluctuations of constraints (Davids, 2014). Due to the inter-relatedness of constraints it is likely that the presence, or modification, of one constraint will influence the structure of other constraints (Balagué et al., 2019). Constraints also emerge and decay across multiple time scales of learning, performance and development (Newell et al., 2001) and exist across multiple levels of analysis (Pol et al., 2020). The interactive nature of constraints increases the complexity for understanding emergent movement as a dependent property of contextual information. This conceptualisation of constraint interaction positions the CLA as complex, where components interact non-linearly along various spatiotemporal scales (Balague et al., 2013). The non-linear nature of a complex system implies that small changes in one constraint may lead to large re-organisation of an entire system. Accordingly, it is important that sport practitioners evaluate constraints in context with one another. This may improve their interpretation and avoid over or under valuing their influence when considered in isolation.

Literature examining constraint interaction is limited. This is due in part, to the reductionist paradigm which has been persistent in skill acquisition literature (Pol et al., 2020) but also to the methodological challenges the complexity of constraint interaction poses on researchers (Browne et al., 2021; Glazier, 2017; Robertson et al., 2019a). Literature which has considered constraint interaction is prevalent across numerous sports however, has generally been limited bivariate examinations. For example, in soccer, team coordination may be influenced by the interaction of field dimensions with skill level (Silva, Duarte, et al., 2014) or the number of players (Silva et al., 2015). Technical actions are influenced by interactions between number of players and game type (Abrantes et al., 2012), pitch surface type and playing position (Brito et al., 2017), or scoring mode and player age (Almeida et al., 2016). In field hockey, the interaction of game type and the number of players increased or decreased player actions according to the task goals and the available space (Timmerman et al., 2019). In long jump, kinematic changes during running emerged from interactions between performance environment and task goal manipulations (Panteli et al., 2016). Although limited, this body of work highlights the interactive nature of constraints on the emergent properties of individual and team behaviours in sport.

Recent studies in AF have exemplified how measuring a greater quantity of constraints can reveal important non-linear constraint interactions (Browne, Sweeting, et al., 2019; Browne et al., 2020; Robertson et al., 2019a). One study compared a univariate analyses of isolated constraints with a non-linear multivariate model including six constraints (Browne, Sweeting, et al., 2019). It was shown that, compared to a multivariate model, a univariate analysis was misleading for evaluating kicking performance. However, as more constraints were included in the multivariate model (Fig 2.2), non-linear associations were revealed which provided a more comprehensive evaluation of kick success (Browne, Sweeting, et al., 2019). A similar study performed a multivariate analysis of Rugby place kicking and discovered only two constraints, kick distance and angle, were significant contributors to predicting kick success (Pocock et al., 2018). However, these findings may be limited by the utilisation of a linear analysis incapable of measuring non-linear constraint interactions. Constraint interaction is evidently a pertinent aspect to the CLA to understand emergent movement. Moreover, considering a larger quantity of constraints is beneficial given an appropriate analytical technique is used. Regardless, the interaction of task, environmental and individual constraints should be considered by practitioners in the design of learning environments during the process of skill acquisition. Tools which assist coaches to consider constraint interaction may improve their practical implementation of the CLA.

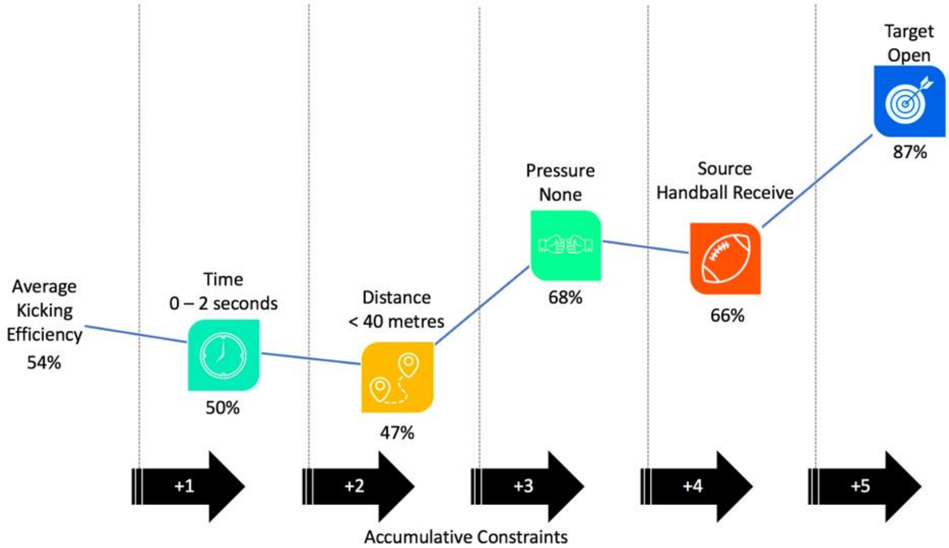


Figure 2.2 An example of accumulative constraint interaction influencing kicking effectiveness in Australian Football (Browne et al., 2019)

2.3 Skill Acquisition: Implications for sport practitioners

The theory of ecological dynamics presents a contemporary perspective on the emergence of coordinated movement patterns in neurobiological organisms (Davids et al., 1994). The CLA, underpinned by ecological dynamics, is useful to provide a framework for understanding the features which shape skilled and coordinated behaviour (Davids et al., 2008). Given the emphasis on constraints and the utility of self-organisation within human movement systems, the CLA holds new and important implications for strategies of skill acquisition (Renshaw et al., 2010; Renshaw & Chow, 2019; Woods, McKeown, O'Sullivan, et al., 2020). Such implications for enhancing skill acquisition are relevant for a number of domains including high performance sport (Farrow & Robertson, 2017; Woods, McKeown, O'Sullivan, et al., 2020) and physical education (Renshaw et al., 2010; Renshaw & Chow, 2019; Rudd et al., 2021). This is important for physical educators, coaches or sport practitioners who are responsible for the education and facilitation of movement and skill development in their students or athletes.

An implementation of the CLA supports a non-linear pedagogical framework which places the athlete at the centre of the learning process (Chow, 2013; Renshaw et al., 2009). A non-linear pedagogy can complement the CLA by providing principles relevant to the practical execution and structure of learning activities (Chow, 2013; Correia et al., 2019). This learning paradigm contrasts with the principles of traditional skill acquisition theories which promote rote repetition to strengthen neural pathways (Wulf & Lewthwaite, 2016). A non-linear pedagogy, grounded in ecological dynamics, emphasises a mutual and reciprocal relationship between the organism and the environment where the aim is for the learner to establish deep couplings with the environment (Renshaw et al., 2009). Accordingly, this pedagogical approach encourages the careful manipulation of constraints to design learning environments which may achieve this (Chow, 2013).

2.3.1 Learning designers

During skill acquisition, a learner establishes deep and adaptable relationships with the environment (Woods, McKeown, Rothwell, et al., 2020; Woods, Rudd, Gray, et al., 2021). Accordingly, the emphasis for the instructor facilitating skill development is education of attention. Contrasting with traditional theories, a non-linear pedagogy suggests appropriate learning environments guide a learners exploration of their perceptual-motor landscape towards areas of relevant information which regulate action to achieve the intended task goal (Chow et al., 2011; Chow, 2013; Davids, 2012; Renshaw et al., 2010). As learners are permitted to explore, over time, they develop deep coupling tendencies with affordances used to guide movement. This tendency, or predispositions for actions, are known as intrinsic dynamics (Davids, 2014). When intrinsic dynamics are aligned with critical information in the performance environment, effective transfer of learning can occur (Davids, 2014). Indeed, it is the information-action relationship which transfers from practice tasks to competition (Araujo & Davids, 2011). This has also been referred to as building knowledge *of* a task instead of knowledge *about* a task (Gibson & Carmichael, 1966). Indeed, learning environments should be designed exclusively to attenuate or magnify affordances and build perception-action relationships (Davids, 2012). This perspective emphasises a relational worldview of emergent behaviour and skill learning (Gibson, 2014; Gibson & Carmichael, 1966; Woods, Rudd, Gray, et al., 2021; Woods & Davids, 2021). It centres the learning process as one where learners engage meaningfully with their environment, through a process of exploration, to self-regulate their actions and decisions (Woods, Rudd, Robertson, et al., 2020; Woods, Rudd, Gray, et al., 2021; Woods & Davids, 2021). Indeed, learning has been positioned as inseparable from dwelling and inhabiting a landscape of dynamic affordances to establish functional behaviours in relation to their environment (Woods, Rudd, Gray, et al., 2021).

To support this learning process, ecological dynamics re-positions sport instructors and coaches as “learning designers” (Davids, 2012, 2014; Woods, McKeown, Rothwell, et al., 2020). This re-positioning shifts the focus of practice from the instructor, imparting knowledge directly to the learner, to one where practice environments and tasks are constructed which can guide the learner to explore solutions to movement problems (Woods, McKeown, Rothwell, et al., 2020). The concept of the coach as a learning designer gives the learner autonomy and enables the discovery of individualised movement solutions (Chow, 2013). Accordingly, the role of the coach is to enhance the self-discovery of the learner through the careful construction of learning environments. The manipulation of constraints during dynamic tasks are intended to set up conditions where athletes are guided towards critical information sources, without explicitly providing solutions (Handford et al., 1997). This outlook on coaching has been termed “hands-off coaching” due to the softer pedagogical influence of the instructor (Davids et al., 1994; Davids, 2014; Handford et al., 1997; Woods, McKeown, Rothwell, et al., 2020). This shifts coaching away from verbal instructions or explicit directions and towards a deep understanding of the learners’ interaction with the environment (Handford et al., 1997; Woods, McKeown, Rothwell, et al., 2020).

Importantly, viewing the coach as a designer should not be misconstrued as a de-emphasis on the practitioner role. It may be interpreted that the practitioner has no place in the learning process but can let the “game be the teacher” (Renshaw et al., 2016; M. O. Sullivan et al., 2021). In such an approach the aim is to simply expose learners to game-like environments to improve their technical and tactical skill capabilities (Renshaw et al., 2016). There is little input from the instructor and less value is attributed to individual differences. On the contrary, learning and understanding during non-linear pedagogical practice occurs through engaging with an affordance rich taskscape, with space for self-regulation within the guiding influence of an experienced practitioner (Woods, Rudd, Robertson, et al., 2020; Woods, Rudd, Gray, et al., 2021). The coach's role remains as an integral component in the learning process but is re-conceptualised from a prescriptive source of knowledge to a guide and facilitator (Woods, Rudd, Gray, et al., 2021). Previously the coaching role was analogous to a GPS device, explicitly directing an athlete towards a destination. Contrastingly, the coaching role as a designer is required to nudge athletes towards critical landmarks which may inform the path towards their destination (Woods, Rudd, Robertson, et al., 2020). Critically, within this analogy, there is not one optimal route but several paths an athlete may explore to meet their goal. Coaches, educators and practitioners may lean on principles of a non-linear pedagogy to inform how a "hands-off" coaching approach may be implemented. Opportunities exist to support sport practitioners to achieve the implementation of a non-linear pedagogy. A key method to achieve this occurs through constraint manipulation.

2.3.2 Constraint manipulation

Through the lens of the coach as a learning designer a common strategy, and a critical skill, to enhancing skill development is the manipulation of constraints (Renshaw & Chow, 2019). In practice activities, constraints may be modified in such a way as to inhibit or encourage an athlete to perceive important information which may be used to regulate actions and decision making (Chow, 2013; Renshaw et al., 2010; Renshaw & Chow, 2019). This commonly involves the implementation or modification of task constraints. Constraint manipulations have been applied to influence a range of outcomes including to improve individual movement kinematics (Shafizadeh et al., 2019; Verhoeff et al., 2018), increase or decrease technical and physical outcomes (Bonney et al., 2020; Fleay et al., 2018; Timmerman et al., 2019), improve decision making capabilities (Vaeyens et al., 2007), influence the spatial interaction of players at a team level (Abrantes et al., 2012; Owen et al., 2011) or improve rehabilitation activities in return to play athletes (Allen et al., 2021). Indeed, coaching through the manipulation of constraints has been shown as more effective at developing skill than other methods including differential learning or prescriptive instructions (R. Gray, 2020; Komar et al., 2019).

The goal of constraint manipulation is to guide athletes to pick-up key information which is used to regulate movement (Renshaw & Chow, 2019). Their manipulation should magnify or attenuate specific affordances within the performance environment (Passos et al., 2008). For example, in a 1v1 situation in Rugby Union, interpersonal distance was a constraint which influenced passing or running decisions in attackers (Passos et al., 2012). Accordingly, widening a field of play may accentuate the gaps between defenders, promoting attackers to recognise and exploit them. Constraints may be manipulated using systematic or unsystematic methods (Orth et al., 2019). Systematic manipulation changes specific constraints intended to guide the attention of athletes towards more optimal solutions or specific intended behaviours. For example, the use of an analogy was an effective informational constraint to improve the efficiency of arm-leg coordination patterns during breast-stroke practice (Komar et al., 2019). Unsystematic manipulation is used to promote variability in behaviour to encourage exploration and the development of degeneracy (Orth et al., 2019). This aligns closely with concepts of differential learning where the aim is to perturb a learner's movement solutions through random fluctuations in task constraints (R. Gray, 2020; I. Schollhorn et al., 2012). For example, random adjustments in posture, equipment sizes or weights or interpersonal distances can improve a learner's explorative processes requiring them to continuously adapt to new circumstances. Accordingly, such an approach achieves "repetition without repetition" (Ranganathan et al., 2020). Coaching within a CLA should be viewed as an ongoing task, involving the continuous manipulation of constraints throughout the dynamic learning process (Pol et al., 2020). However, applied research which can support this process is limited. Opportunities exist to support practitioners to evaluate constraint manipulations, in the field, to inform their efficacy.

Some important caveats to the implementation of a CLA do exist. Firstly, constraints should only be manipulated to guide or nudge the attention of the athlete towards such affordances, while maintaining space for exploration of alternative options (Renshaw & Chow, 2019). Over-constraining a task will not promote adaptable, self-discovered solutions but enforce them (Renshaw & Chow, 2019). Additionally, there is a tendency in sport to manipulate skills through a global-to-local direction, such as in imposed tactical structure or plan (Ribeiro et al., 2019). Coaches should also not neglect the bi-directional self-organising processes of their athletes and look for opportunities to facilitate skill development through local-to-global directions. This is advantageous to promote degeneracy and develop adaptable performers (Ribeiro et al., 2019). Further, manipulating task constraints should always appreciate the pre-existing intrinsic dynamics of the individual (i.e. their individual constraints) (Orth et al., 2019; Renshaw et al., 2016) and the interaction of constraints in the environment.

To evaluate the efficacy of a practitioner’s constraint manipulations, a learner’s behaviour should be measured according to non-linear pedagogical skill acquisition principles (Chow, 2013; Chow et al., 2011). Given the implications for movement educators, a non-linear pedagogy has been explored most frequently in the areas of athlete development (Chow, 2013; Renshaw et al., 2009) and in physical education (Rudd et al., 2020). A non-linear pedagogy can provide a rationale for evaluating effective training design. For example, variability can hold a functional role in skill performance (Davids, Glazier, et al., 2003) and can be viewed as functional exploration of the learner as they search for optimal solutions (Newell & McDonald, 1992). Variability in movement performances can show an effective adaptation to changing constraints to achieve goal-orientated tasks (Davids, Glazier, et al., 2003; Seifert et al., 2013). Thus, effective constraint manipulations in practice may encourage variable performance from athletes. Similarly, faithful simulation of performance environments promotes effective skill transfer and is known in the literature as “representative learning design” (Pinder et al., 2011). Detailed sampling of variables available during competition is key to inform training environments (Davids, 2014). To support constraint manipulations during practice which can transfer to competition, athlete behaviour may be compared to competition to identify similarities, or dissimilarities (Browne et al., 2020; Ireland et al., 2019; Tribolet et al., 2022).. The principles within a non-linear pedagogy will inform the goals of practice which frame evaluations of practice design (Chow, 2013; Chow et al., 2011; Renshaw et al., 2009). Importantly, supporting coaches to evaluate athlete behaviour according to such skill acquisition principles would guide their decisions regarding constraint manipulations.

In one method to effectively implement a CLA which adheres to non-linear pedagogical principles, practitioners have been encouraged to utilise small sided games (Davids et al., 2013). Games based training is often implemented by coaches to enhance skill and develop physical capacities (Gabbett et al., 2009). Indeed, small sided games have also been shown as equally effective for aerobic improvements as isolated running drills (Impellizzeri et al., 2006). Small sided games have been presented as a viable opportunity to coach with a hands-off approach (Davids et al., 2013). Small sided games allow for continuous inter and intra team interactions while providing appropriate opportunities for information-movement coupling (Davids et al., 2013). The nature of small sided games maintains relevant match affordances during the practice tasks enhancing the transferability of skills to competition. The structure of small sided games may be easily modified by practitioners to accentuate or dampen constraints in the athletes task, such as number of players (Aguiar et al., 2015; Bonney et al., 2020; Vilar et al., 2014), field dimension (Fleay et al., 2018; Frencken et al., 2013; Timmerman et al., 2017) or task goals (Cordovil et al., 2009; Timmerman et al., 2019; Travassos et al., 2014). Small side games are advantages over full size games as they allow specific sub-phases of play to be represented providing increased frequency of opportunities for specific actions or time spent in particular scenarios (Davids et al., 2013). Additionally, in full size games, the increased number of players allows for more compensatory interactions to occur decreasing the tendency for the system to destabilise. Thus, small sided games promote more destabilisation of coordinated movement patterns, enhancing the adaptability and degeneracy of team coordination. A final benefit to the use of small sided games is they will likely present a more enjoyable opportunity for training, enabling more time spent in engaging activities (Davids et al., 2013). Tools which focus on supporting the design of small sided games are critical to facilitate skill development in team sports.

Given the important theoretical insights of the CLA and the practical principles of its implementation through a non-linear pedagogy, designing practice is a challenging proposition for coaches, physical educators and sport practitioners (Orth et al., 2019). The process of coaching has indeed been proposed as analogous to athletes exploring and attuning to their perceptual environments, requiring time and practice to develop expertise (Orth et al., 2019). Furthermore, the dense academic language of these concepts are perceived as a barrier for practitioners (Renshaw & Chow, 2019). Accordingly, the CLA has seen limited uptake from coaches (Stone et al., 2021). However, the implementation of effective practice environments is a critical factor to enhancing skill development and driving performance (Williams & Ford, 2009). In sport literature, there is a gap in applied research which supports coaches to implement a CLA to enhance athlete skill acquisition. To meet this need, there are opportunities to harness data and analytics to evaluate practice and inform training design according to skill acquisition principles of the CLA.

2.4 Informing training design

To inform training environments and support coaches as learning designers, within the CLA, it is essential to gain an understanding of athlete behaviour in such environments. In sport, evaluating athlete performance can occur for many purposes including talent identification (Larkin et al., 2020; Vaeyens et al., 2008), team selection (Iyer & Sharda, 2009) or where human judgement is required to determine performance outcomes, such as figure skating or diving (Looney, 2004; Osório, 2020). In invasion style team sports, such as football or AF, the game is dynamic and complex with varying components interacting on different time scales (Balague et al., 2013; Gudmundsson & Horton, 2017). Therefore, it is difficult for coaches or domain experts to recall specific events or plays, including these large volumes of information that occur within invasion sports (Borrie et al., 2002). Further, coaches' evaluations of talent are subjective and may lack reliability (Roberts et al., 2020) and performance judges have shown biases in their evaluations (Looney, 2004). Accordingly, to understand sport performance, practitioners have sought to measure behaviour through objective methods. This is achieved by retrieving information which is normally unattainable with the coaches eye to enhance their observations (Borrie et al., 2002). Further, To overcome such biases, tools have been developed, such as decision support systems, to support the interpretation of information (Schelling & Robertson, 2020). These objective tools may also be integrated with subjective interpretations (McIntosh et al., 2019). However, the application of similar tools to inform training design, within a CLA, remains largely unexplored. With the rise in objective data in sport, the discipline of performance analysis has emerged.

2.4.1 Performance Analysis

Performance Analysis is a sub-discipline of sport science. Originally stipulated as a combination of biomechanics and notational analysis, performance analysis has since included disciplines of motor control (Hughes, 2004). The purpose of performance analysis is to advance the understanding of game behaviour with the purpose of improving future performances (McGarry, 2009). Performance analysis has been utilised extensively across a variety of sport types including net and wall, striking and fielding and invasion (Hughes & Bartlett, 2002). Through the collection and analysis of data, key indicators of performance, such as the frequency of important events or behaviours, have been developed. These indicators may evaluate biomechanical, technical, and tactical aspects of team and individual performance. For example, frequencies of winners and errors provide insight into the technical performance of a player in tennis or squash while the number tackles won or lost can indicate tactical underpinnings in soccer (Hughes & Bartlett, 2002). Such insights are presented to inform corrections or modifications to playing style or provide critical insight into opposition game structures which may be exploited. Common procedures within the discipline of performance analysis involve the use of video technology, systematic techniques of recording reliable observations and providing feedback to other practitioners, coaches and athletes (Bartlett, 2001). Literature has also explored how to improve the visual analysis of observational match data to enhance the interpretability for practitioners (G. Andrienko et al., 2017; Ryoo et al., 2018). To build upon this, the application of these techniques may also be used to inform training design.

A specific technique implemented by performance analysts is notational analysis. Notational analysis is the process of objectively quantifying behaviours that relate to the technical and tactical performance of players and teams (McGarry, 2009). It involves the manual notation of sequential events or behaviours, typically recorded in a discrete manner. Historically, such information was gathered using pen and paper methods, involving the scripting of live events as they occurred which could subsequently be tallied (O'Donoghue, 2009). However, the advancement of technology has greatly facilitated this process with the development of computer based annotation software or video tracking systems (O'Donoghue, 2009). The information gathered through notational analysis typically pertains to *who, what, where* and *when* (McGarry, 2009). Notational analysis is used to collect data which may support coaches and sport practitioners in identifying performance trends. Importantly, notational analysis should provide complimentary information which is not already perceived by practitioners (Bartlett, 2001). Performance analysis can use notational data to develop key performance indicators which may support coaches in evaluating performance (Mackenzie & Cushion, 2013). This information is used to support coaches to inform decision making and draw relationships between behaviours and performance. However, opportunities exist to improve the application of performance analysis through a theoretical framework such as the CLA.

2.4.1.1 Performance Analysis underpinned by a constraints-led approach

Whilst the field of performance analysis has revealed further understanding to many aspects of a sport, it has come under critique due a lack of an underpinning theoretical rationale guiding it's processes (Glazier, 2010; McGarry, 2009). The relationships between indicators and performance cannot be appropriately established without an underlying theory to interpret the data (Vilar et al., 2012). The performance indicators typically utilised to evaluate performance have been suggested as descriptive rather than explanative (Hughes & Bartlett, 2002; McGarry, 2009). For example, events such as passes or shots, are recorded with the exclusion of contextual information such as the field location or dyadic player interactions (McGarry, 2009). This has positioned the field of performance analysis as reductionist in nature, attempting to reduce the understanding of human movement to particular outcome variables. Such rudimentary observations are unable to explain *how* or *why* such actions have occurred (Glazier, 2010; Vilar et al., 2012). Accordingly, a theoretical framework could enhance how performance analysis could be applied in sport (Glazier, 2017).

Sport has been described as a complex system where behavioural outcomes are the emergent result of interactions between critical system components (Balague et al., 2013; Davids, 2014). To account for this, theories such as complex systems, dynamical systems or ecological dynamics have been suggested as suitable to underpin the work of performance analysis (Glazier, 2010; McGarry, 2009; Vilar et al., 2012). Such rationales recognise the complexity and non-linearity of dynamic interactions within sport environments. Accordingly, the consideration of interacting contextual information is a key tenet to evaluating emergent behaviour appropriately (Newell, 1986). It has been suggested that the CLA is an appropriate theoretical framework due to its roots in ecological dynamics but involves less dense academic language which is more accessible to the practitioner (Glazier, 2010). Although the CLA was originally positioned to conceptualise the emergence of organismic motor patterns, the principles have application in the analysis of individual and team performance within complex sport environments. Constraints form the boundaries of the system which shape the emergence of stable behavioural patterns (Newell, 1985). Thus, information pertaining to the constraints on sport actions have important implications for *how* or *why* such actions occurred and provide a deeper understanding of performance.

Technology may augment the application of performance analysis within the CLA. Technology has been suggested as a useful tool to support the skill development process (Browne et al., 2021; McCosker et al., 2021; Woods, Araújo, et al., 2021). However it's application should be considered carefully as its misuse may hamper learning (McCosker et al., 2021; Woods, Araújo, et al., 2021). Technology should be used to augment or complement a learner's experience and be used as a tool to guide or question a learner's behaviour. Accordingly, technology should be used to support how learners engage directly with the environment to support their perception of critical information (Woods, Araújo, et al., 2021). Within training, technology may be utilised via equipment modifications, athlete movement tracking, video-based feedback or enhancements to performance analysis techniques (McCosker et al., 2021). Specifically, technology can be harnessed to improve measures of constraints or enhance the analysis of constraint interaction (Browne et al., 2021). In this vein, opportunities exist to build upon this work, harnessing technology and data to improve the application of performance analysis within the CLA. Such insights, when applied within a practice environment, can improve how coaches and practitioners evaluate learning activities.

The discipline of performance analysis may be applied to inform training design. This work may be guided by the underpinning theoretical framework of the CLA. Accordingly, the field of performance analysis presents important techniques and opportunities to collect and analyse data pertaining to athlete behaviour. This may be harnessed to support coaches and sport practitioners to facilitate skill development and enhance performance.

2.4.2 Enhancing the application of the constraints-led approach

Data and analytics may be harnessed to improve the implementation of the CLA. In recent years, in sport there has been an exponential increase in the collection of data relating to performance at team and individual levels (Rein & Memmert, 2016). Importantly, given the conceptual framework of the CLA, the sampling of detailed constraint information is essential for appropriately evaluating player behaviours. This information may support the design of learning environments and consequentially, enhance sport performance. To improve the implementation of the CLA, and inform sport training design, sport practitioners may seek to leverage data and technology to i) increase the quantity of constraints, ii) improve the measurement of existing constraints and/or iii) improve the techniques used to analyse constraints.

2.4.2.1 Increased quantity of constraints

The more constraints which can be included in a model, the greater our understanding of how constraints are shaping performance (Robertson et al., 2019a). From a theoretical perspective, understanding of a dynamical system is incomplete if important constraints or context which shapes it is unknown (Balague et al., 2013). In a comparison of univariate, bivariate and multivariate constraint analysis, the multivariate approach had more explanatory power given the inclusion of more constraints in the model (Browne, Sweeting, et al., 2019). To achieve sampling of additional constraints, analysts may be guided by coaches or expert practitioners. Coaches have vast experience in their specific sport with high levels of declarative and procedural knowledge (Nash & Collins, 2006). This experiential knowledge can be used complimentarily to enhance analytical methods (Greenwood et al., 2014). Specifically, it has been suggested that the expertise of coaches be harnessed to identify key constraints which shape the performance of athletes during training and matches (Greenwood et al., 2014; Pocock et al., 2020). Additionally, identifying which constraints are unable to be modified is important too (Renshaw & Chow, 2019). For example, interviews with coaches were able to identify 11 important task, environmental and individual constraints which influence the difficulty of place kicking in Rugby Union (Pocock et al., 2020). It has also been suggested that performers in the environment are an additional rich source of information which should not be overlooked (Woods, Rothwell, et al., 2021). Accordingly, athletes are intelligent learners whose experience can be utilised to assist in identifying key constraints which are shaping their behaviours. This information can be practically utilised by coaches to inform training design manipulations but may also serve as a source for performance analysts to identify key constraints which require measurement. Importantly, this process involves blending empirical and experiential knowledge which has been suggested as useful to inform practice design for sport performance (Woods, McKeown, O'Sullivan, et al., 2020).

However, adding more constraints is not always the most effective solution to modelling their influence on performance. The measurement of more constraints usually increases the burden upon resources to collect this information. This investment should be cost effective. In analytics this concept is known as parsimony (Browne et al., 2021). Parsimony relates to the balance of the quantity of variables included in a model with the explanatory power of a model. Thus, if variables included in a model do not substantially increase the accuracy of the model's predictions, they can be removed. Although this may involve small reductions in the accuracy of the model, it increases the feasibility of data collection by reducing the quantity of necessary variables. The concept of parsimony is beneficial in complex sport environments where collecting large amounts of information is a challenge for practitioners (Browne et al., 2021). Measuring a greater quantity of constraints, while considering parsimony, may enhance the feasibility of applying the CLA to inform training design.

2.4.2.2 Improved measures of constraints

Given the theoretical implications of the CLA, performance analysts have sought to measure contextual information to inform player behaviour evaluations. Specifically, the technique of notational analysis has been applied to manually record contextual information pertaining to constraints on skilled actions during sport performance. For example, in AF, constraints such as pressure, possession time, opposition density or movement speed, have been collected and compared between competition and training environments (Browne et al., 2020; Ireland et al., 2019; Woods, McKeown, et al., 2019). Similarly, constraints on kicking in elite and sub-elite competitions have also been compared to highlight performance demand differences (Browne, Sweeting, et al., 2019; Woods, Jarvis, et al., 2019). In Rugby, manually notated constraints such as, kick distance or angle to goal, influence the success of place kicking (Pocock et al., 2018) and long jumping (McCosker et al., 2019). Thus, important insights have been gained through the application of notational analysis to collect constraint information. However, opportunities exist to further improve these measurements.

Whilst informative, the manual notation of events is laborious and prone to errors due to its subjective nature. Indeed, accurate measurement and analysis of constraints may be a challenge for practitioners due to the multi-levelled and abundant number of constraints (Glazier, 2017). For example, a commonly recorded constraint shown to be important in shaping skilled performance is time (Browne, Sweeting, et al., 2019; Browne et al., 2020; Ireland et al., 2019; Pocock et al., 2018; Woods, McKeown, et al., 2019). However, to simplify the collection of this constraint via notational analysis, this measure has been allocated into temporal epochs, such as brackets of one or two seconds (Browne, Sweeting, et al., 2019; Woods, McKeown, et al., 2019) or ten minute intervals (Pocock et al., 2018). A more feasible method to collect this constraint could improve it through a continuous measurement. Accordingly, with continuous measurements, more precise insights may be gained during analysis.

In sport there are increasing opportunities to exploit technologies to increase the feasibility and accuracy of data collection. Specifically, harnessing technology can potentially improve the quantity and/or quality of constraint information without increasing the burden on the practitioner to manually record the information. It has been suggested that technology and analytics have scope to improve how the implementation of the CLA in sport may be achieved (Browne et al., 2021; Glazier, 2010, 2017; McCosker et al., 2021; McGarry, 2009; Vilar et al., 2012; Woods, Araújo, et al., 2021). Specifically, the use of technology to automatically detect movement or actions can improve the accuracy or reliability of measures which are manually recorded. For example, the implementation of athlete-worn inertial measurements sensors have seen an increase in sport application to detect movements (Cust, Sweeting, Ball, & Robertson, 2019). This technology has been applied to automatically record actions such as kick types (Cust et al., 2021), tackles (Chambers et al., 2019) and to quantify strokes in swimming (Fulton et al., 2009a, 2009b). Additionally, marker-less motion trackers have been used to quantify and grade player changes of direction in tennis match play (Giles et al., 2020). Further, the use of player tracking technology is common practice in many sport codes (Gudmundsson & Horton, 2017). The automatic and continuous tracking of players movements can be accurately and objectively determined (Gudmundsson & Horton, 2017). Determining player movement patterns by automatically detecting their spatial and temporal location on a playing field has been achieved through computerised vision and wearable sensors and used to gain important tactical insights (Castellano et al., 2014; Giles et al., 2020; Gudmundsson & Horton, 2017). The implementation of such technology could be similarly used to measure key constraints in the sport performance or practice environment, when guided by the CLA.

A particular example of a constraint which may benefit from improved measurement is pressure. Pressure is a highly prevalent concept in sport (G. Andrienko et al., 2017). Many metrics used to measure pressure have focussed on the physical presence of opponents on the field of play. The presence of opposition acts as a constraint on available space and time afforded to players and is generally considered to influence movements and actions. Pressure may be measured during crucial moments of skilled behaviour, such as catching or kicking a ball or as a general tactical strategy implemented throughout match play (G. Andrienko et al., 2017). The quantification of physical pressure has occurred through various methods. Using notational analysis, pressure measurements have been allocated to skill events according to the location of the opposing players. This is achieved by recording the location of the opposing players (e.g. frontal or chase) if they are within a given perimeter to the ball carrier at the moment of skill execution (Browne, Sweeting, et al., 2019; Ireland et al., 2019). This location may also be graded according to the distance (e.g. <5m or 5-15m) to the player with the ball (Ireland et al., 2019; Timmerman et al., 2017, 2019). Alternatively, the quantity of opposition players in nearby proximity has also been used to measure pressure on the passer and also the passing receiver (Woods, Jarvis, et al., 2019; Woods, McKeown, et al., 2019). Measuring pressure via notational analysis has been useful for analysts and practitioners and some evidence exists to support it's validity, specifically, it has been associated with unsuccessful kick outcomes in AF (Browne, Sweeting, et al., 2019). However, notational analysis retains a level of subjectivity which carries a margin of error during annotation. Thus, leveraging technology to automatically and objectively record this information may improve pressure measurement. Further, notational analysis provides a categorised value, which only considers the players within the immediate proximity of the ball carrier. The development of continuous metrics for pressure may be advantageous in measuring the constraint to determine it's influence on skilled behaviour.

2.4.2.3 Analysing constraints

Analytics can be leveraged to find relationships within data by harnessing the mathematical computational power of machines. This can overcome limitations to human processing by considering larger volumes of information and can alleviate human factors such as bias (Robertson & Joyce, 2019). Historically, performance analysts dealt with a paucity of information to explain sport performance however, in recent years data has become increasingly available (Rein & Memmert, 2016). The result is large, high dimensional datasets which may serve as a rich information source for analysts. Accordingly, there has been an increase in the application of non-linear, multivariate analytical techniques, such as data mining or machine learning, in sport (Dutt-Mazumder et al., 2011; Horvat & Job, 2020; Rein & Memmert, 2016). Specifically, due to the complexity of the sports environment and the abundance of data, enhanced analytical techniques are applicable to improve our understanding of the CLA (Browne et al., 2021). Such techniques are beneficial for sports analysis for two reasons. Firstly, on a practical level, given the increase in dataset sizes there is a need for analytical techniques which can cope with high volumes of variables (Browne et al., 2021). Indeed, the more constraints which can be measured the deeper the understanding of the system structure (Balague et al., 2013). In sport analyses of rich contextual information is essential to understanding how individual and team coordinative behaviour emerges. Secondly, from a theoretical perspective, according to the CLA constraints do not act in isolation but interact dynamically and non-linearly (Davids et al., 2008). Thus, univariate, or linear approaches cannot appropriately measure constraints and their interaction with one another. This is important for practitioners to avoid over or under valuing a constraint when considered within a larger constraint group. To this end, there is a need to utilise non-linear techniques, such as machine learning or data mining, to understand the complexity of sport environments. Enhancing the practical application of such analytical techniques can support the design of training and the implementation of the CLA in sport.

2.4.3 Sport data and analytics

To inform the design of training environments, data may be collected and analysed within the guiding framework of the CLA. Various data types are regularly collected in sport including event data, spatiotemporal data and physical output data. The integration and appropriate analyses of this data may provide deeper insights into player behaviour. This may support the field of performance analysis and enhance the application of the CLA by increasing the quantity of constraints collected or improving their measurement or analysis.

2.4.3.1 Event data

Through the technique of notational analysis, objective observations of certain events are gathered to inform aspects of performance in a variety of sports. Such forms of data are often referred to as event data. In team sports, event data has commonly been analysed to provide frequency counts or ratios, which are indicative of technical or tactical behaviour (Hughes & Bartlett, 2002). This data has been used to enhance the understanding of team or individual performance which can be exploited by coaches or practitioners to improve match outcome. For example, event data has been used to measure aspects of team tactics in team sport (Hughes & Franks, 2005; Wedding et al., 2021; Woods, Robertson, et al., 2017). Particular tactical approaches may be adopted by coaches from the analysis of team performance trends, as seen in event data recorded during the FIFA World Cup (Hughes & Franks, 2005). Further, the longitudinal progression of league wide playing styles has been evaluated (Woods, Robertson, et al., 2017) and tactical approaches between teams differentiated (Wedding et al., 2021) through analyses of key event data. To inform coaching strategies the key skill event indicators, related to winning or scoring in sports, including men’s AF (Robertson et al., 2016), women’s AF (Black, Gabbett, Johnston, et al., 2019; Cust, Sweeting, Ball, Anderson, et al., 2019), Rugby Sevens (Higham et al., 2014), Rugby League (Woods, Sinclair, et al., 2017) and soccer (H. Liu et al., 2015) have been profiled. Event data has also been used in evaluating individual player performance during competition (McIntosh et al., 2018b, 2019) and has other uses such as distinguishing between player roles and positions (McIntosh et al., 2018a), . To build upon the insights provided with event data, other data types, such as spatiotemporal data, may be collected to further contextualise individual and team performance.

2.4.3.2 Spatiotemporal data

Important contextual information during sport play is the location of events (i.e. passes or shots) or players, and their physical interaction in the playing area (Correia et al., 2012; Orth et al., 2014;

Passos et al., 2012). Spatiotemporal, or tracking, data describes the location of players or events in physical space and time (Gudmundsson & Horton, 2017). The use of spatiotemporal data is important to contextualise event data and provide further insights into tactical information (Glazier, 2010). Spatiotemporal data may be recorded as a global position (latitude and longitude) or as x and y cartesian coordinates relative to the court or field. Locational data is also timestamped at varying rates, commonly between 10-30 Hz (Gudmundsson & Horton, 2017) which results in a database with the time and the location of all players on the field. Two types of spatiotemporal data exist: object tracking or event logs. Object tracking involves the continuous capture of the location of objects, such as players and balls. Event logs involve the recording of field or court locations and times for specific events, such as shots or passes (Gudmundsson & Horton, 2017). Modern technology presents useful automated or semi-automated methods to analyse player movements (Rein & Memmert, 2016). Integrating player tracking technology may enhance player and team evaluations and may be applied to inform training design.

Advancements in spatiotemporal data have seen increased adoption of tracking technology in sport (Rein & Memmert, 2016). Multiple technologies exist to track objects including wearable devices such as global positioning systems (GPS), local positioning systems (LPS) or computer based motion analyses of video footage (G. Andrienko et al., 2017; Barris & Button, 2008; Gudmundsson & Horton, 2017). For GPS or LPS systems, players are required to wear devices on their bodies, usually within a custom harness between their shoulder blades (Sweeting et al., 2017). These systems do have an advantage over vision-based systems, which are unable to discern individual players. This is a common issue in invasion sports such as Rugby or American Football (Gudmundsson & Horton, 2017). Vision based technologies are capable of determining the location of players and/or sport articles (e.g. the ball). Although many tracking systems exist, mean error margins for player spatial locations in some systems have been reported at 23cm, 96cm and 56cm for LPS, GPS and video technology, respectively (Linke et al., 2018). This highlights the importance of using a single system for reliable data collection. A caveat to data collected from some systems, particularly GPS or LPS, is that they are unable to identify the orientation of players however, such information may been inferred by analysing consecutive tracking samples to determine direction (Spencer, Jackson, et al., 2019). Furthermore, the validity and reliability of these technologies to also measure player distances and speeds have been reviewed, encouraging their use in research and performance analysis (Barris & Button, 2008; Buchheit et al., 2014; Castellano et al., 2014).

The adoption of spatiotemporal data analysis, has been encouraged to support the field of performance analysis (Glazier, 2010). Specifically, spatiotemporal data may be used to help contextualise match event data. For example, in basketball, shot charts are commonly used to detail trends in shot locations which may provide teams with a tactical advantage during match play or inform the shot types to focus on during practice (Reich et al., 2006). Similarly, continuous object tracking provides the location of players at regular intervals throughout an entire match. This may be analysed to determine player relationships to teammates, opponents, the ball and the field. It is possible to evaluate aspects of performance such as time spent in field areas, team spatial control or pressing tactics (G. Andrienko et al., 2017; Gudmundsson & Horton, 2017). In team invasion sports, performance cannot be wholly understood without reference to complex movements and interactions of players on the field (Gudmundsson & Horton, 2017).

In team invasion sports, such as football, the movement of all players on the field is complex and changes frequently. Although complex, teams are composed of independent degrees of freedom which can form synergies to behave as a single functional unit (Araújo & Davids, 2016). Coordinative units (i.e. groups of players) can exhibit synergistic attributes such as dimensional compression or reciprocal compensation (Glazier, 2017). Here, many degrees of freedom (i.e. players) are capable of self-organising into stable behavioural patterns or performing compensatory movements to maintain a particular coordinative state (Araújo & Davids, 2016; Glazier, 2017). Accordingly, measuring the synergistic attributes of team behaviour gives insight into the individual players' inter and intra team regulatory tendencies (Vilar et al., 2012). Spatiotemporal data, derived from tracking equipment, has been analysed to achieve this, measuring the physical interaction of players on a field in sports including soccer (Frencken et al., 2011, 2013; O'Brien-Smith et al., 2021; Silva, Duarte, et al., 2014), field hockey (Timmerman et al., 2017), basketball (Bourbousson et al., 2010, 2014) and AF (Alexander, Spencer, Mara, et al., 2019; Alexander, Spencer, Sweeting, et al., 2019). Within this literature, various metrics have been demonstrated, such as dispersion or synchrony, which can measure collective team behaviour. Opportunities may exist to leverage such metrics to evaluate team behaviour and inform training design.

Some metrics which have been developed are useful for measuring the dispersion or compression of a team. This is useful to determine how players regulate the physical space between one another. To achieve this, the relative positioning of players on a field may be measured at each relevant time point and then subsequently summarised to give an overall or an average for a time period, such as a match or quarter. Some examples of these metrics include stretch index (O'Brien-Smith et al., 2021), surface area (Clemente, Couceiro, Martins, Mendes, et al., 2013) or density (Spencer et al., 2017). Stretch index was calculated as the average distance of each player to their team's geometric centre (O'Brien-Smith et al., 2021). Similarly, surface area was calculated as the area within the boundary created by the outermost players and has been closely correlated with stretch index (Clemente, Couceiro, Martins, & Martins, 2013). Density was calculated using a kernel density estimation algorithm to determine the spread of players throughout the field (Spencer et al., 2017).Additionally, effective area involves calculating the area that a team covers which is not intercepted by an opponent (Clemente, Couceiro, Martins, & Martins, 2013). Finally, the dominant regions for each player on the field refer to the areas which a player can reach before any other (Taki et al., 1996). This is useful for determining the space on the field which is "owned" or controlled by a team. Sub-dividing the playing field according to dominant regions and subsequently summing their areas is an alternate measure for the spatial dispersion or compression of a team (Fonseca et al., 2013; Gudmundsson & Horton, 2017). These metrics each measure different aspects of team dispersion or compression and may be flexibly applied to determine tactical trends. However, team coordination may be influenced by other contextual factors within match play.

To form coordinative behaviour, players regulate their movement according to the positioning of one another (Araújo & Davids, 2016). However, the structure and organisation of a team is also dependent upon various match factors. For example, team behaviour variables are influenced by the phase (e.g. attack or defence) of play (Alexander, Spencer, Mara, et al., 2019; Alexander, Spencer, Sweeting, et al., 2019; Frencken et al., 2011; Sheehan et al., 2021), first half vs second half (Clemente, Couceiro, Martins, Mendes, et al., 2013), current score (Clemente et al., 2014), field area (Alexander, Spencer, Sweeting, et al., 2019) and numerical imbalances (Alexander et al., 2021). Accordingly, external constraints may shape the coordinative structures of players on the field, influencing the inter-player interactions. Through the lens of the CLA, a practitioner may seek to leverage external task constraints by manipulating them to guide their players towards more optimal organisational structures (Renshaw & Chow, 2019). For example, team behaviour has been influenced by skill level (O'Brien-Smith et al., 2021; Silva, Duarte, et al., 2014; Silva, Travassos, et al., 2014), playing number (Aguiar et al., 2015; Silva, Travassos, et al., 2014; Silva, Vilar, et al., 2016; Timmerman et al., 2017), field dimensions (Frencken et al., 2013; Silva, Duarte, et al., 2014), area per player (Silva, Vilar, et al., 2016; Timmerman et al., 2017) and the number of targets (Travassos et al., 2014). Furthermore, improved spatiotemporal synergies of team mates have been developed through practice (Silva, Chung, et al., 2016). This evidence suggests that the CLA is an appropriate framework to analyse and facilitate collective team behaviour.

Given the prevalence of player tracking technology in sport, spatiotemporal datasets are now large and rich in detail (Rein & Memmert, 2016). This has led to the development of models which estimate different parameters in performance. For example, motion models are built using information pertaining to field location, current velocity and orientation of each player on the field to evaluate the spatial ownership of players and teams at any given moment during matches (Fernandez & Bornn, 2018; Gudmundsson & Wolle, 2014; Spencer, Hawkey, et al., 2019). This has tactical value by revealing which teams or players owned larger or higher valued territory during key moments during a match. Additionally, such datasets may be combined with manually annotated match event data to give detailed contextual information to player actions. This has led to the development of models which assign a value to player or team actions. For example, in soccer, models have been developed which automatically evaluate passing performance (Horton et al., 2015), estimate moments of potential scoring opportunities (Link et al., 2016) or determine the likelihood of shot success (Lucey et al., 2014). Further, risk-reward profiling has been achieved by evaluating the difficulty of passes in reference to the potential benefit based upon the field location and scoring opportunity (Power et al., 2017). In AF, to evaluate decision making, similar risk and reward models have been developed (Spencer, Jackson, et al., 2019) and passing has been evaluated against all potential options to determine if the most optimal decision was made (Spencer et al., 2018). Together, this work demonstrates how novel analytical models have been advantageous for providing objective evaluations of player and team performance. However, the development of new metrics to evaluate player behaviour has not been applied to support training design. A specific area of application in analysing spatiotemporal data may be to improve the measure of pressure.

Given the advancement of player tracking in sport, there are opportunities to utilise the spatiotemporal data derived from such technologies to develop new methods of pressure measurement. Synchronising spatiotemporal data with match event logs means it is possible to determine the location of players during key events, such as shots or passes. Pressure has previously been quantified in this way by calculating the distance of players to the ball (Taki et al., 1996). This method had been critiqued due to the exclusion of player direction in the model (Gudmundsson & Horton, 2017). Other spatiotemporally derived pressure metrics have used distance, orientation and angle of goal to build models which may quantify pressure constraining the player with the ball (G. Andrienko et al., 2017; Link et al., 2016). Each of these models are advantageous for determining a numerical measure of pressure which can be analysed continuously. This may improve the measure beyond manual notation methods which use categorised data. Additionally, sampling of the data can occur automatically and objectively, relieving the burden on human resources and improving the reliability of the measure. Thus, the integration of spatiotemporal data has multiple applications to enhance the implementation of the CLA in sport.

2.4.3.3 *Physical output data*

In high performance sport the measurement of physical output is widely accepted to improve physical capacities such as aerobic conditioning and minimise the risk of injury associated with over-training (Buchheit & Simpson, 2017; Burgess, 2017). Although the relationship between output and injury is debated (Carey et al., 2018) it remains an important facet to high performance sport programs. Furthermore, measures of physical output may be used to infer levels of fatigue which may constrain coordination tendencies (Davids et al., 2000; Glazier, 2017; Rodacki et al., 2001). Thus, it’s measurement is also valuable to performance analysts as contextual information for player evaluation (Glazier, 2017). Physical output monitoring is achieved through a variety of objective and subjective measures such as rating of perceived exhaustion, heart rate monitoring and distances run (Borresen & Lambert, 2008). A common technique in research and applied sport science is the implementation of player tracking devices. Player tracking devices have been used extensively to measure the external work demands of players during match play (Aughey, 2010; Clarke et al., 2018; A. Gray & Jenkins, 2010; Mooney et al., 2011; C. Sullivan et al., 2014). This may inform the design of training environments (Chandler et al., 2014), inform long term periodisation (Haff, 2010) or determine worst case scenario workloads (Fereday et al., 2020). Physical player output may also be relevant to movement coordination as compensatory actions have also been observed in fatigued athletes seeking to maintain a performance outcome (Bonnard et al., 1994; Dorel et al., 2009). Accordingly, physical output measures may be used to contextualise individual and team performance evaluation (Glazier, 2017).

Many facets of external workload or work rate can be determined using player tracking devices. For example, absolute measures such as total distance or max velocity (A. Gray & Jenkins, 2010), or time relative measures such as metres per minute or high intensity metres per minute (Aughey, 2010; Mooney et al., 2011; M. O. Sullivan et al., 2021) may be used. Typically, velocity is discretised into “bands” or “zones” which can represent paces for walking, jogging, running or sprinting (A. Gray & Jenkins, 2010). Accordingly, time or distance accumulated by players in each zone may be reported and can be used to evaluate work rate. Alternatively, other measures such as frequency or distances of accelerations can be derived from player tracking technology (Sheehan, Tribolet, Spurrs, et al., 2020). Although the measures for external load are numerous, methods to reduce the complexity of key variables have been demonstrated to relieve the burden on sport practitioners (Oliva-Lozano et al., 2021; Sheehan, Tribolet, Spurrs, et al., 2020). Furthermore, the implementation of GPS or LPS player tracking devices are useful to measure player output during small sided training games (Bonney et al., 2020; Fleay et al., 2018; Nunes et al., 2021; Timmerman et al., 2017, 2019). Indeed small sided games are an effective training modality to improve aerobic capacity and skill development simultaneously (Gabbett, 2006; Impellizzeri et al., 2006). Thus, measuring player output allows practitioners to consider the physical constraints alongside the skilled behaviours of players to inform training design. However, physical output is typically determined on an individual level, without reference to constraints which may shape player movements. To build upon this further, physical and skilled behaviours may also be considered within time.

2.4.3.4 Time series

A common technique in sport performance evaluation is the use of aggregate measures. Aggregate measures may summarise individual or team actions across seasons (Woods et al., 2018) or matches (Woods, Robertson, et al., 2017). Within matches, performance has also be aggregated into periods, such as halves or quarters (Cust, Sweeting, Ball, Anderson, et al., 2019), the phase of play (Rennie et al., 2020) or on field stints (Corbett et al., 2017). For example, total match distance may be used to evaluate an individual's physical load or the volume of skill involvements to measure skilled performance. While the use of such metrics has given valuable insight into describing player performance or developing key performance indicators they are insensitive to the fluctuations in behaviour which may have occurred over time. Analysing sport performance as a function of time provides contextual information which may reveal deeper insight into how or why events have occurred (Glazier, 2017). In AF, players reduce their physical and technical output following periods of peak intensity during match play (Black et al., 2016) or during the second half of match play (Black, Gabbett, Naughton, et al., 2019). In soccer, first half activity levels are inversely related to second half activity levels (Sparks et al., 2016). Rugby place kick success is also reduced in the 10 minutes prior to half time (Pocock et al., 2018). Accordingly, time sensitive analytical techniques are appropriate when evaluating sport performance.

Time series analyses can be applied to sequentially obtained data to measure it's change (Cryer & Chan, 2008; Fu, 2011). To this end, player output is typically reported as sub-sets of match duration. For example, player output has been analysed using predetermined periods such as five minute blocks in soccer (Carling & Dupont, 2011) or eight minute blocks in AF (Black, Gabbett, Naughton, et al., 2019). However, discrete pre-determined time periods underestimate peak intensity, by up to 25% compared to rolling windows, and should therefore be interpreted with caution (Varley et al., 2012). Subsequently, rolling time windows have been applied across a range of durations, between one and ten minutes, to measure physical and skilled performance in Rugby (Delaney et al., 2015, 2016) and AF (Black et al., 2016; Delaney et al., 2017). To build upon this work, the analysis of time-series data in a continuous manner may be advantageous.

In sport, time series analyses may benefit from continuous analytical techniques. Sport research has primarily analysed subsets of a sequence according to pre-determined periods or rolling windows of varying durations (Black et al., 2016; Delaney et al., 2017). Although such analytical techniques have been useful, any measures which exist outside of the time windows are excluded from analysis. To further inform the insight which time series analysis can provide, continuous measures may be advantageous as they consider the entire data sequence rather than subsets of it. However, continuous time-series analyses have rarely been applied in sport. This may be due to the more complex nature of continuous analytical techniques or perceptions of difficulties in communicating findings to key stakeholders (Browne et al., 2021). One example from AF applied a continuous time series segmentation technique to potentially identify more optimal interchange moments during match play (Corbett et al., 2019). This approach was beneficial for dividing player's velocity profiles into unequal segments without relying on pre-determined durations.

Specifically, change point detection involved identifying time points in a time series where statistical characteristics meaningfully change (Killick & Eckley, 2014). Users may specify parameters of the algorithm including the number of change points to search for, the statistical property to evaluate, and may apply penalties to increase or decrease the sensitivity of change point detection (Aminikhanghahi & Cook, 2017; Killick & Eckley, 2014). Change point detection has been applied widely in other fields such as medical monitoring, climate change or speech recognition (Aminikhanghahi & Cook, 2017). Previously, such analyses have been limited to univariate approaches however, recent advances to change point detection permit multivariate analysis (Bardwell et al., 2019). This approach combines multiple sequences into a single time series with multiple observations. Thus it allows the integration of simultaneously occurring time series to determine their interaction as a function of time. Such a technique is advantageous in sport where many observations of physical, tactical and skill data occur (Stein et al., 2017). Accordingly, multivariate techniques would allow the integration of different data types to evaluate a single match or activity (Browne et al., 2021; Glazier, 2017). Continuous time series analytical techniques, such as change point detection, remain unexplored to evaluate training. However, continuous time series analyses are supported within the framework of the CLA.

To further support the continuous analysis of temporal data, a key tenet of the CLA is that constraints emerge and decay along multiple time scales of performance, learning and development (Newell et al., 2001). This refers to multi-levelled dynamical systems which evolve and interact across varying time-scales such as, years, weeks, hours or seconds. More simply constraint time-scales have been termed structural (slow changing) or functional (fast changing) (Balagué et al., 2019). Examples of slow changing constraints include personality, anthropological measurements or gravity which contrast with fast changing constraints such as fatigue, player positioning or weather (Balagué et al., 2019). Changes in constraints may not be isolated to a single time scale but distributed across many (Wijnants et al., 2012). Analysis of constraints as a function of time is pertinent to appropriately contextualising performance. Accordingly, the framework of the CLA encourages the use of continuous time-series analytical techniques. Moreover, the utilisation of more sophisticated multivariate analytical techniques may further the understanding of constraints to inform training design.

2.4.3.5 Analytical techniques

To enhance the implementation of the CLA in sport it may be beneficial to improve the analysis of various sport data types. This may include the application of multivariate analytical techniques, such as machine learning or complex statistical techniques. Machine learning is the process of discovering and identifying novel trends or patterns within datasets (Horvat & Job, 2020; Ofoghi et al., 2013). Machine learning algorithms can be grouped into supervised, unsupervised or reinforcement learning categories, within which, a number of analytical techniques fall, including regression, rule association, classification and decision trees (Mohammed et al., 2016). Such techniques can search through large datasets to determine non-linear patterns or build models for outcome predictions. Specifically, machine learning algorithms are capable of identifying patterns, determining variable interaction and building models to predict outcomes based upon associated relationships learned from historical, or exemplar, data (Mohammed et al., 2016; Zhang, 2020).

In supervised machine learning, an algorithm is trained with a dataset of predictor variables labelled with associated outcomes (Mohammed et al., 2016; Zhang, 2020). Given this, the algorithm can learn trends and patterns within the data which are related to outcomes specified by the user. These learned relationships are often then applied to previously unseen sets of data to make predictions. Examples of supervised techniques include regression models or decision trees (Fahrmeir et al., 2013; Loh, 2011). In contrast, unsupervised approaches are not trained with a dataset labelled with outcomes. Accordingly, the algorithm is tasked with discovering important patterns and features which exist within the data without prior knowledge of correct outcomes. Examples of unsupervised techniques include clustering or rule association (B. Liu et al., 1998; Solanki & Patel, 2015). Many problems in sport are treated as class prediction, such as win/loss or goal/miss, or numerical prediction, such as forecasting score lines (Horvat & Job, 2020). Thus, supervised and unsupervised techniques are often applied in sport to suit such classification and regression tasks (Horvat & Job, 2020). Furthermore, the utility of (un)supervised techniques, including rule association or decision trees, to visualise and communicate constraint interaction in sport has been demonstrated (Browne et al., 2022). Although supervised and unsupervised classes represent most machine learning techniques, some approaches may be classed as semi-supervised if they fall between criteria. Alternatively, a final branch of machine learning is reinforcement learning, where models are trained through a trial and error process, however, this has seen limited applications in sport (Horvat & Job, 2020).

An advantage of machine learning is the ability to measure the non-linear interaction between multiple variables. Within motor learning and skill acquisition, the dominant type of research design has been limited to laboratory tasks. In such tasks experimental rigour is maintained at the loss of constraints which reflect the sport performance setting (Wulf & Shea, 2002). Typically, only one or two constraints are measured and manipulated. To develop a deeper, and more accurate, understanding of sport performance there has been a call for more scientific studies to be conducted within practical real-world environments (Newcombe et al., 2019). Technology and analytics may be harnessed to help collect and analyse data in these messy and noisy environments (Newcombe et al., 2019). Importantly, according to the CLA, constraints do not act in isolation but are interactive in nature, where the presence of one will likely influence another, and their confluence results in non-linear movement outcomes (Newell, 1986). Considering constraint interaction is pertinent to understanding sport performance and facilitating skill development through the design of training environments. As the feasibility of constraint collection increases in sport, with the advancement of technology and resources, including improved computer processing power, there is a need for advanced analytical techniques which can address the interaction between constraints, especially considering the exponential number of relationships which may exist (Robertson et al., 2019a). Data mining and machine learning algorithms are capable of measuring such interactions and can leverage upon advanced computing power to process increased data resolution (Browne et al., 2021).

The application of machine learning has been explored in AF, specifically using association rules and decision trees, to measure the interaction of constraints which shape kicking outcomes (Browne, Sweeting, et al., 2019; Browne et al., 2022; Robertson et al., 2019a). This type of analysis was able to determine which constraints commonly occur together and which sets of constraints are associated with effective or ineffective performance outcomes. A rule association analysis was also used to build a classification model where kick outcomes could be predicted, with 70% accuracy, according to the set of constraints present (Robertson et al., 2019a). This research progressed to explore constraint interaction across sequences of passes to compare the skill involvements in training activities with competition (Browne et al., 2020). In Rugby, constraint interaction has been measured using binomial logistic regression models to predict place kick outcome (Pocock et al., 2018). Of the five independent variables included in the model, it was shown that place kick success was most influenced by distance and angle to the goal (Pocock et al., 2018). Accordingly, this analytical method was additionally useful for determining which constraints were most valuable for explaining kick outcome. Thus, machine learning techniques permit a deeper understanding of the CLA and there is scope to build upon previous work to provide practical tools which may inform training design. One specific technique which may be applied is rule association.

One commonly implemented unsupervised learning technique is Rule Association. Rule association, or rule mining, are algorithms that are able to discover interesting relationships between variables (Agrawal et al., 1993; Agrawal & Srikant, 1994). Rule association is easily interpretable as it closely resembles the human process of heuristics. Rule association can be applied to transactional datasets to discover the items which most frequently occur together. A simple example of this algorithm can be seen in supermarket basket analysis (Agrawal et al., 1993). Retail companies have harnessed the insights gained from rule association to determine trends in consumer purchases, such as which items are typically purchased together (Solanki & Patel, 2015). An example statement from a supermarket basket analysis may be that 90% of customers who bought milk and eggs, also bought bread (Agrawal et al., 1993; Agrawal &

Srikant, 1994). Rule mining has also seen applications in other domains such as medicine or stock analysis (Altaf et al., 2017; Solanki & Patel, 2015). Two important measures in rule association are support and confidence. Support is the frequency of a given rule within a dataset while confidence is the likelihood that the rule is true. The most commonly implemented rule association algorithm is the Apriori algorithm (Agrawal et al., 1993). When executing the Apriori algorithm, the user can specify limits to parameters, such as support and confidence, to constrain the amount of rules which are produced. This filters the rules to find the most important ones for the user. Rule association can also be augmented through the integration of a classification approach (Nguyen et al., 2012, 2012). This approach can train a model using an example data set to predict class outcomes given the set of mined rules. This model can then be applied to new data to make classification predictions.

In AF, rule association has been implemented to evaluate player kicking during match play (Browne, Sweeting, et al., 2019; Browne et al., 2020; Robertson et al., 2019a). The Apriori algorithm was used to determine the interaction between up to six constraints which may influence kicking (Browne, Sweeting, et al., 2019; Robertson et al., 2019a). This analysis provided a way to measure kicking during match play to inform how representative learning environments could be designed during practice. This analysis was expanded to include temporally sequenced events, such as passing chains in AF, and was enhanced with an integration of a classification based on association approach to model predictions (Browne et al., 2020). This approach was useful to draw comparisons between small-sided games, match simulations and competition play. Rule association has also been applied in netball to discover frequently recurring passing trends to provide deeper match insight for performance analysts and coaches (Browne, Morgan, et al., 2019). There is an opportunity to build upon this work to evaluate player behaviour during training as a tool to support practitioners in their training design.

Regression analysis is another commonly implemented supervised approach to estimate the relationship between a single outcome variable and numerous explanatory variables. Specifically, the dependent variable of interest is modelled as a response to a set of independent covariates

(Fahrmeir et al., 2013; Welc & Esquerdo, 2018). Accordingly, regression models may be built to predict outcomes. Different types of regression models exist and are predominantly classified according to the explanatory data type such as, continuous, ordinal, or binary (Welc & Esquerdo, 2018). Regression models can range from simple, when only one explanatory variable is used, to multiple, where numerous explanatory variables are related to the outcome. Regression analysis has multiple uses including prediction, parameter estimation and model specification (Gunst & Mason, 2019). Furthermore, regression models are capable of determining how covariates interact to influence an outcomes prediction (Fahrmeir et al., 2013).

Linear regression models are advantageous given their flexibility to handle multiple data types and thus, have been widely applied in fields such as economics (Harvey et al., 1986), epidemiology (Suárez et al., 2017) and real estate (Ghosalkar & Dhage, 2018). However, linear regression models assume linear relationships (Gunst & Mason, 2019) and thus, their application to non-linear problems, such as the nature of sport, is limited. Despite this, linear regression models have seen useful applications in sport. For example, regression models have been used to predict performance outcome in Rugby League (Woods, Sinclair, et al., 2017), the model the age effects on skill and physical adaptations in soccer (Fransen et al., 2017), or the predict place kick outcome in the Rugby Union World Cup. Indeed, the last example demonstrates a modelling approach within a CLA framework. Model prediction was explained with constraints such as kick distance, angle to goal, time of game or previous kick success (Pocock et al., 2018). However, given the theoretical insights of the CLA (Newell, 1986), a non-linear analytical technique approach would be more useful to determine the interaction effects between constraints. Such approaches may provide more accurate models giving practitioners a deeper insight into athlete behaviour.

Decision trees are a popular non-linear machine learning technique which involve the prediction of a single outcome variable using several predictor variables (De'ath & Fabricius, 2000). Decision trees can be used for classification purposes, to make predictions on categorical data, or using regression, to predict continuous data (Loh, 2011). Classification and regression trees work by recursively partitioning a dataset, one variable at a time, into homogenous and mutually exclusive groups. Each partition splits the dataset into two groups, which are in turn partitioned uniquely into two groups again (Gupta et al., 2017). The recursive partitioning technique considers interaction between features of the dataset (Morgan et al., 2013). Accordingly, branches are grown, where each branch represents a rule defined by the splits in variable values. Branches are continually grown until the predictive power of further splits no longer improves the model (Morgan et al., 2013). This technique is useful given its flexibility to incorporate various data types including categorical, numerical and missing data and is advantageous for producing an easily interpretable visual output for the end user (De'ath & Fabricius, 2000). However, caution should be exercised as decision trees are prone to over-fitting which may limit their predictive accuracy when applied to new data (Morgan et al., 2013) The application of decision trees, similar to other machine learning techniques, commonly involve training a model (building or growing the branches) using a training dataset and subsequently applying this model to predict outcomes on an unseen dataset.

Decision trees have been applied in a range of sport settings. For example, random forest models have been grown for the purpose of automatic movement classification using wearable sensors in AF (Cust et al., 2021) or computer vision in tennis (Giles et al., 2020). Random forest models have also been applied to sport injury diagnosis (Zelič et al., 1997) and prediction (Carey et al., 2018) however, with limited success. Regression trees have been applied to individual AF match play statistics to predict player ratings (McIntosh et al., 2019), predict shot outcome (Browne et al., 2022) or to predict the outcomes in 1v1 situations, based on spatiotemporal characteristics of the players, in field hockey (Morgan et al., 2013). Finally, conditional inference trees have seen limited success in predicting skilled involvements according to on-field stint duration and physical running parameters (Corbett et al., 2017). Accordingly, decision trees may be a viable tool for sport analyses however their application in AF practice environments has not been demonstrated.

2.5 Australian Football

AF is a complex invasion style sport (Pill, 2014). To compete at the elite level players are required to have a high capacity for physical output while maintaining effective skill involvements (Johnston et al., 2018). The free-flowing nature of the game, unlike other codes such as rugby or American football, the lack of distinct phases increases the difficulty of analysis (O'Shaughnessy, 2006). Research within AF is broad with studies ranging from elite men and women competitions, sub-elite and junior players. Predominantly, research in AF has focussed on developing a deeper understanding of match play while literature which has examined AF practice has remained limited.

A number of descriptive studies have examined skilled and/or physical behaviour during match play. In AF, performance analysis techniques have been applied to identify trends or key performance indicators during matches. Such studies have highlighted the evolution of gameplay over several seasons (Lane et al., 2020; Woods, Robertson, et al., 2017) or aggregated measures over entire matches (Black, Gabbett, Johnston, et al., 2019), quarters (Cust, Sweeting, Ball, Anderson, et al., 2019) or phases of play (Rennie et al., 2018, 2020). This has been further broken down into positional differences (Clarke et al., 2018; Dawson et al., 2004b). Further comparisons have been drawn across competition tiers including elite, sub-elite and junior (Browne, Sweeting, et al., 2019; McIntosh et al., 2021; Woods, Jarvis, et al., 2019). The descriptive profiling of competition demands has been useful to provide benchmarks or standards which can inform training requirements.

To further profile the behaviours of players and teams during competition, spatiotemporal data has been used. Spatiotemporal data derived from player tracking devices has been explored extensively to determine team interaction tendencies and tactical trends within the context of influential match factors such as phase of play (Alexander, Spencer, Mara, et al., 2019; Spencer et al., 2017) or field position (Alexander et al., 2021; Alexander, Spencer, Sweeting, et al., 2019). Additionally, methods have been demonstrated which can model player decision making and evaluate choices according to risk and reward ratios (Spencer, Jackson, et al., 2019) or alternative options (Spencer et al., 2018). To improve the practical application of complex data, methods to simplify many variables to explain key components in tactical and physical performance have been demonstrated (Sheehan et al., 2021).

Deeper insight into AF match play has been revealed through novel applications of analytical techniques. This has been used to enhance performance analysts in their development of key performance indicators. For example, a change point analysis was used to identify potentially more optimal interchange locations by identifying time points in player velocity profiles where a meaningful change occurred (Corbett et al., 2019). Rule association, a branch of machine learning, has been applied to identify the most commonly occurring sets of constraints on kicking in AF matches (Browne, Sweeting, et al., 2019; Browne et al., 2020; Robertson et al., 2019a). Such insights can be used to inform the design of training environments which mimic competition. Principle component analysis has been applied to reduce the dimensions of variables which are used to describe aspects of player or team performance including skill (Sheehan, Tribolet, Watsford, et al., 2020a), physical (Sheehan, Tribolet, Spurrs, et al., 2020), or team interaction (Sheehan et al., 2021, 2022; Sheehan, Tribolet, Watsford, et al., 2020b). These sophisticated analytical techniques have shown valuable insight into understanding match play however their application into AF training is yet to be explored.

A range of AF studies have drawn comparisons between practice environments and competition environments to determine training specificity. It has been shown that running demands and technical action frequencies differ between the two playing formats (Dawson et al., 2004a; Ireland et al., 2019). Differences also exist in constraints on technical involvements, such as pressure or possession time (Ireland et al., 2019) and cooperative passing networks (Tribolet et al., 2022). Although insightful, the reported discrepancies may not translate to other teams or competition tiers, and can not be applied to other sports. Accordingly, tools have been developed, and exemplified in AF, to identify where and to how much training differs from competition (Browne et al., 2020; Corbett et al., 2018; Woods, McKeown, et al., 2019). Multiple techniques have been demonstrated including magnitude based analysis (Woods, McKeown, et al., 2019), specificity index (Corbett et al., 2018; Woods, McKeown, et al., 2019), K-means clustering (Corbett et al., 2018), or a classification based on association approach (Browne et al., 2020). The classification based on association was advantageous for its consideration of constraint interaction and temporal sequencing of events (Browne et al., 2020). Although such tools are useful for measuring the differences between training activities and matches, they have limited capability to inform which constraints should then be manipulated by practitioners. Thus, tools which may evaluate constraint manipulations in AF may guide the design of training activities which promote player behaviour more representative of competition.

Research which has examined AF practice has been less extensive than match play. Due to this, there is limited insight for AF coaches in the construction of appropriate learning environments. Indeed, the CLA has been specifically proposed as a supportive framework to analyse AF and inform practice activities (Pill, 2014). In agreement with CLA principles it was shown that open AF drills, which are more dynamic representations of competition, were more cognitively and physically demanding than closed drill types (Farrow et al., 2008). Despite the important influence of the CLA, limited studies have examined the influence of constraints on skilled AF player behaviour. In some notable exemptions, creating an attacking outnumber can increase kicking efficiency and decrease the proportion of kicks to covered players (Bonney et al., 2020). Alternatively, increasing the field size during a small side game increased the physical output and reduced the occurrence of technical actions such as tackles and turnovers (Fleay et al., 2018). In an examination of cooperative networks, it was shown that during small side games, the frequency of shots on goal is positively correlated with team connectedness (Tribolet et al., 2021). Accordingly, designing practice tasks which encourage shots on goal can promote team interaction tendencies. Although this work is insightful, the generalisability to other participant groups, such as other competition tiers or teams, is limited. More AF research which can exemplify practical tools for sport practitioners and coaches would be useful.

2.6 Summary

Practice is essential for the development of sport skills (Ericsson & Smith, 1991; Howe et al., 1998). Although this is evident in the literature, there is still much that is unknown about the best methods to structure practice tasks which optimise skill development. To appropriately guide practice design decisions, the CLA, a contemporary conceptualisation of motor control, is suitable to frame this problem (Newell, 1986). The CLA approach is grounded in ecological dynamics which conceptualises the performer and the environment as a complex and dynamical system, with many interacting components (Davids et al., 1994; Handford et al., 1997). Constraints form boundaries of the performer-environment system and shape the coordinative structures of emergent actions. Accordingly, this framework holds important implications for practitioners, positioning them as learning designers who construct appropriate practice environments through the manipulation of constraints (Chow et al., 2011; Woods, McKeown, Rothwell, et al., 2020). A key tenet to the CLA is that constraints do not act in isolation but interact, non-linearly, with one another to influence behaviour. Accordingly, constraint interaction is a prominent consideration in the application of the CLA for designing training environments in sport. Within sport science and performance analysis, there is scope to improve the collection and analysis of constraints to more effectively evaluate player behaviour in a manner which supports coaches and sport practitioners (Browne et al., 2021). This process may involve the measurement of additional constraints, improving the measure of existing constraints or enhancing the analysis of constraint interaction. Specifically, this application within practice environments remains limited. Many forms of data are routinely collected in the sport landscape which are useful for evaluating player behaviour including event data, spatiotemporal data, or physical load data (Rein & Memmert, 2016). Sophisticated analytical techniques, such as machine learning algorithms, may be applied to integrate such data sources and measure constraint interaction. Harnessing technology and analysis may be useful to provide tools which can assist practitioners inform training design.

CHAPTER THREE – STUDY I

Chapter Overview

Chapter Three is the first of five studies contained in this thesis. Physical pressure is an important constraint which may shape many behaviours in team sports. Thus, this thesis first sought to improve the measurement of the constraint of pressure to understand it's influence on skilled athlete behaviour. Specifically, this study explores how spatiotemporal analysis of player tracking data may be used to determine a continuous measurement for the constraint of pressure.

The content of this chapter is an accepted manuscript of an article published by Taylor & Francis in Journal of Sports Sciences on 3rd July 2021, available at: http://www.tandfonline.com/10.1080/02640414.2021.1886416

JOURNAL OF SPORTS SCIENCES
2021, VOL. 39, NO. 13, 1548–1554
https://doi.org/10.1080/02640414.2021.1886416

Routledge
Taylor & Francis Group

SPORTS PERFORMANCE

OPEN ACCESS Check for updates

Application of a continuous pressure metric for Australian football

Ben Teune[a,b], Bartholomew Spencer[a], Alice J Sweeting[a,b], Carl Woods[a], Mathew Inness[a,b] and Sam Robertson[a]

[a]Institute for Health and Sport, Victoria University, Melbourne, Australia; [b]Football Department, Western Bulldogs, Melbourne, Australia

ABSTRACT
Pressure is an important constraint on sports performance and is typically measured through manual notational analysis. A continuous representation of pressure, along with semi-automated measurement, would serve to improve the efficiency of practice design and analysis, as well as provide additional context to player competition performance. Using spatiotemporal data collected from wearable tracking devices, the present study applied Kernel Density Estimation to estimate the density of players, relative to the ball carrier, at point of skill execution during elite Australian Football training. Two environmental constraints were measured (*area per player* and *number of players*) to determine the relationship between these training design manipulations and density. Density was also compared with existing notational analysis measurements of pressure. Results indicated that a higher density on skills was associated with successful skill executions. The opposite relationship was found between notational analysis pressure measurement and skill effectiveness. A strong inverse relationship was found between environmental constraint manipulation and density, whereby increasing field size and playing number decreased the density on skill involvements. The findings offer insight into the continuous measurement of pressure and encourage practitioners to utilize training design manipulations to influence density as a constraint on skills.

ARTICLE HISTORY
Accepted 2 February 2021

KEYWORDS
Density; constraints; manipulation; training design; team sport; skill

Introduction

The constraints-led approach (CLA) is a theoretical framework that situates movement as an adaptive property of the performer-environment system (Davids et al., 2008). Constraints act internally and externally to an individual, interacting and changing over time to shape movement and behaviour (Newell, 1986). It is therefore critical, that constraints be measured with sufficient detail and accuracy to gain insight into *how* and *why* particular movements and behaviours emerge (Glazier, 2017; McGarry, 2009). For sport practitioners, the measurement of constraints that shape the behaviour of athletes would likely provide important contextual information for evaluating player behaviour and designing learning environments intended to develop skill (Davids, 2012; Woods et al., 2020). To this end, improving the implementation of the CLA in sport can be achieved through: i) the measurement and consideration of additional constraints, ii) the application of enhanced analytical techniques or, as in the current study, iii) the improved measurement of an existing constraint.

In team sports, a commonly measured constraint is pressure, which is typically defined as the presence of opposition players in a nearby location at the time of skill execution (Andrienko et al., 2017). Given this definition, it is often used interchangeably with density (Link et al., 2016). A common method to measure pressure is to subjectively assign levels (e.g. low, medium and high) via notational analysis, according to the distance between an attacker and the nearest defender during skill execution. This has been applied in basketball (Csataljay et al., 2013) and field hockey (Timmerman et al., 2017, 2019). During futsal shots on goal, the distance of defending players to ball trajectory has also been used as an indicator of pressure (Vilar et al., 2013). In soccer, other methods have utilized spatiotemporal data derived from Global Positioning Systems (GPS), such as distance, velocity, and direction of players, to develop numerical measures for pressure (Andrienko et al., 2017; Link et al., 2016). The majority of pressure metrics have focused on physical pressure, but other construct definitions of pressure have also been reported in the literature. These include situations incentivizing optimal or maximal performance (Baumeister & Showers, 1986), which can manifest through increases in anxiety or emotional responses and thus may negatively impact skill performance (Eysenck, 2013).

In Australian Football (AF), the quantification of pressure has been represented in multiple ways. Types of pressure have been allocated to a skill execution according to the location of defending players, for example, side, frontal, chase or physical (Browne et al., 2019; Ireland et al., 2019; Robertson et al., 2019), along with the number of players within a 3 m boundary to the ball carrier (Woods et al., 2019). Opposition presence around pass receivers has also been recorded as a means of capturing indirect pressure on the passer and direct pressure on the receiver (Browne et al., 2019; Ireland et al., 2019; Woods et al., 2019). Some evidence exists to support the validity of pressure being measured in these ways, specifically due to the association with unsuccessful kicks (between 14.6% and 38.5% efficiency) during AF match play (Browne et al., 2019).

As spatiotemporal data pertaining to players is available in elite AF (with the exclusion of opposition data) there are opportunities to utilize it to improve the sophistication of existing pressure measurements. Thus, a measure of player density was

CONTACT Ben Teune benteune@outlook.com Institute for Health and Sport, Victoria University, Melbourne, Australia

recently developed by applying Gaussian mixture modelling to spatiotemporal datasets during match play (Spencer et al., 2017). This method captured the interaction of all players on the field simultaneously. The work highlighted the changing congestion of players throughout a match, revealing that successful possession chains have large changes in density (Spencer et al., 2017). An adaptation of this type of analysis may provide a valuable metric to improve upon the current measures of pressure by providing a continuous metric. It may also facilitate consideration of the influence of players not within the immediate vicinity of the ball carrier.

The present study seeks to adapt the methodology of Spencer et al. (2017) to use density estimation as a proxy for pressure in AF. The first aim was to determine the extent of the relationship between pressure and the effectiveness of skill involvements. The second aim was to determine the extent to which environmental constraints, as part of training design, influence the pressure on skill execution during training drills. A third aim was to compare pressure derived from density estimation with pressure derived from notational analysis. Establishing these relationships may inform how pressure can be utilized in practice design, while providing additional context to player competition performance.

Methodology

Participants

Participants were listed male players from a single professional AF club (n = 43, 24.2 ± 3.5 y, 186.8 ± 7.7 cm, 84 ± 7.8 kg). All players provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the relevant University Ethics Committee.

Data collection

Data were collected during the 2020 Australian Football League pre-season. A total of 32 training activities were selected for analysis, consisting of eight different drills and 1014 skill involvements (72% handballs and 28% kicks). Drills that were selected were characterized as small sided games (by the club's coaching staff) and consisted of two opposing teams with equal numbers. Team selection was quasi-randomized by the clubs coaching staff to standardize skill level and player experience. The objectives of each drill were nuanced, they generally required teams to score by kicking a goal or completing a pass into a zone at one end of the field. Further, the drills covered all aspects of AF including ball movement, decision making, offensive and defensive actions. Drills ranged from 46.88 m^2 per player to 570 m^2 per player and the total number of players ranged from eight to 20.

To obtain records of each skill involvement, drills were filmed with a two-dimensional camera from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of the drill at the time of performance. To quantify skill involvements and the surrounding task constraints, notational analysis software was used (Sportscode, version 12.2.10, Hudl). A custom code window was created whereby each skill involvement was recorded live, during the session, according to the method (kick or handball) and the outcome (effective or ineffective). Disposal outcome was defined in accordance with Champion Data (Melbourne, Pty Ltd), the commercial statistics provider for the Australian Football League. A handball or kick less than 40 m was deemed effective if the intended target retained possession of the ball. A kick greater than 40 m was deemed effective if kicked to a 50/50 contest or better for the attacking team. Post training, the Sportscode window was used to attribute additional, notational analysis labels to each skill involvement, according to the type of pressure present. Pressure was categorized into four levels; None, Frontal, Chase and Physical (Robertson et al., 2019). These levels were also used to determine a binary pressure measurement by combining Frontal, Chase and Physical into "Present" and using None as "Absent". Coders followed club procedure on "what to look for" when performing notational analysis to ensure consistent interpretations. To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic (Landis & Koch, 1977) was used to assess intra-rater reliability of effectiveness and pressure. Agreement was "almost perfect" for effectiveness (0.93) and binary pressure (0.83) and "substantial" for pressure (0.79). All skill involvement data was exported, according to their drill, into a custom Microsoft Excel spreadsheet.

Spatiotemporal data for each player was collected with 10 Hz GPS units (Vector S7, Catapult, Catapult Sports Ltd, Melbourne). Devices were placed in a vest in a custom pouch between the athlete's shoulder blades prior to the session beginning. Players wore the same device during each session to reduce inter-unit error. During the session, splits were created marking the beginning and end of each activity in the manufacturer's software package (*Openfield*, version 2.5.0). To create a reference point to join skill data with spatiotemporal data, a start label was also coded in Sportscode at the start time of each drill. After session completion, raw spatiotemporal data was exported from *Openfield* into Microsoft Excel for each player and for each training activity. To differentiate teammate and opposition locations, using the recorded footage, each player's spatiotemporal data were arbitrarily assigned a team label for each training activity.

To determine player location for each skill involvement, exported spatiotemporal data and skill involvement data were joined according to their timestamp for each training activity. For both datasets, timestamps were adjusted relative to the beginning of each activity. Latitude and longitude for each player was converted to x and y coordinates, in metres, relative to the ball-carrier position which was set at 0,0. Using assigned teams, each player location was labelled as opposition or teammate, relative to the player performing each skill involvement. Kernel density estimation, a method of estimating the probability density function of a dataset via smoothing of individual points, was used to estimate the density of players at each skill involvement (Simonoff, 1996). The kernel function and bandwidth dictate the shape and smoothness of the resultant probability density function, respectively. Density was estimated using Gaussian kernels and the bandwidth was arbitrarily set to 0.00006 for all samples. A visual example of a sample is presented in Figure 1. Density was calculated across two groups; all players and opposition players only.

To measure constraint manipulation with respect to training design, two environmental constraints were recorded for each training activity. The constraints selected were *area per player* and total *number of players*, which have shown relationships with player density (Silva et al., 2015; Timmerman et al., 2017). Number of players was defined as the total number of players participating in the drill. The area per player was defined as the total playing area of the field, as designated by markers and manually measured before each activity, divided by the number of players. All constraint manipulations for each training activity were recorded and databased in a custom Microsoft Excel™ spreadsheet.

Statistical analysis

All statistical analyses were performed in R (version 3.6.1, Vienna, Austria)using base R functions. Density estimation scores were normalized to the mean, as *z* scores, for both groups: all players and opposition players. To address the first aim, logistic regression models were constructed to determine the relationship between density and skill effectiveness (effective or ineffective). Visual inspection of the distribution of density revealed no substantial differences when considered as only defending players or all players from both teams combined. Consequentially, the remainder of the analysis considered all players from both teams. Three models were constructed; considering either i) only handballs, ii) only kicks or iii) all skill involvements. To address the second aim, a multiple linear regression model was constructed to determine the relationship between the two manipulated environmental constraints (area per player and number of players) and density. To address the final aim, two logistic regression models were constructed to determine the relationship between i) notational analysis pressure according to location and ii) notational analysis pressure as binary (present or absent) and skill effectiveness (effective or ineffective).

Results

For the entire dataset, 83.2% of involvements were effective. Density scores for each involvement were a normalized value, where mean = 0 and SD = 1 and where a higher value represents more density on the skill involvement and vice versa. A visualization of the distribution of density for the entire sample is provided in Figure 2. Logistic regression analysis revealed that for handballs only (B = −0.04, z = −0.334) and for kicks only (B = 0.347, z = 0.976), there was a very weak positive relationship between density and effectiveness. Across all skill involvements, logistic regression analysis revealed that density and effectiveness were positively associated (Model 1 in Table 1). This indicates when density was higher, it was more likely for an effective disposal to occur; however, the association was weak (z = 2.437). Mean density for effective disposals was 0.034 SD and mean density for ineffective disposals was −0.171 SD.

To address the second aim, 32 training drills were analysed. Descriptive statistics are reported as a mean and standard deviation. The mean number of involvements was 31.7 ± 12.2, the mean disposals per minute was 9.9 ± 4.3, the mean number of players was 11.6 ± 3.5 and the mean area per player was 176.9 m^2 ± 165.2 m^2 per drill. Results of the multiple linear

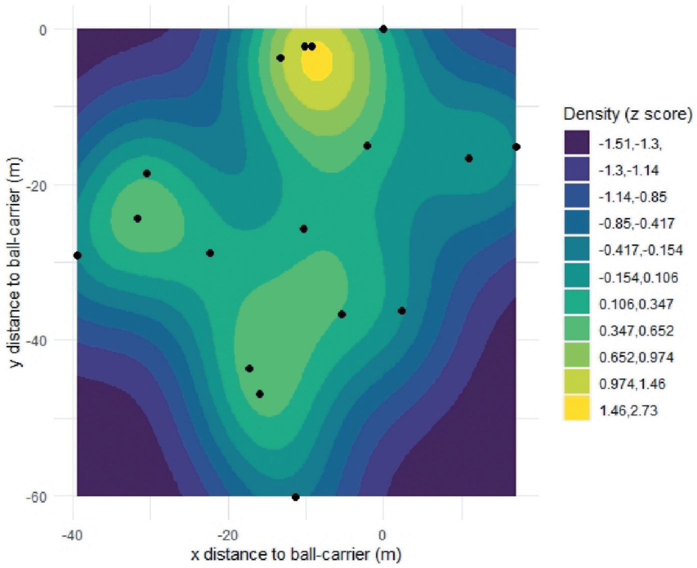


Figure 1. Example representation of a single skill involvement. Points represent player positioning relative to the ball-carrier which is at 0,0. Contours and colour represent density (z score), with positive values indicating higher density.

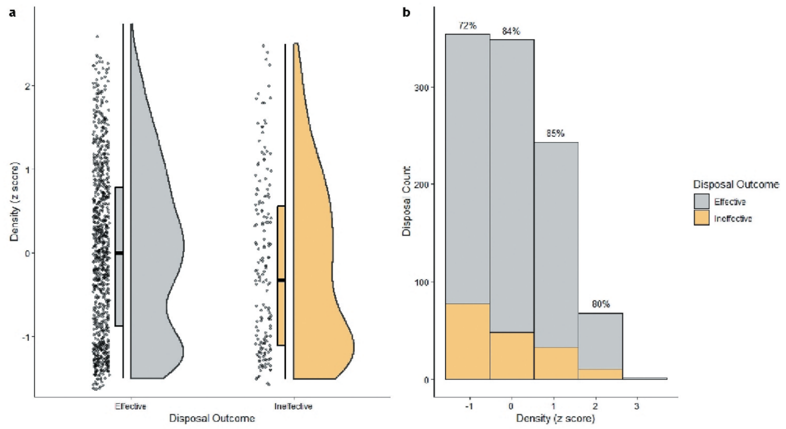


Figure 2. Distribution of density for effective and ineffective skill involvements. A: Each dot represents a single skill involvement. Box and whisker plots indicate the median, interquartile range, minimum and maximum values. Half violin plots represent a continuous distribution of density. B: Histogram bars are stacked according to disposal effectiveness with labels above each bin representing disposal effectiveness (%).

Table 1. Results of logistic regression models. Model 1 shows the relationship between density and skill effectiveness. Model 2 shows the relationship between each level of pressure measured through notational analysis and skill effectiveness. Model 3 shows the relationship between pressure as a binary notational analysis measurement and skill effectiveness. Coefficient and test statistic (z) presented for each variable.

	Effectiveness		
	Model 1	*Model 2*	*Model 3*
Density	0.212* z = 2.437		
Notational Pressure: Chase[a]		−0.328 z = −1.212	
Notational Pressure: Frontal[a]		−0.366 z = −1.798	
Notational Pressure: Physical[a]		−1.147*** z = −4.315	
Notational Pressure: Binary[a]			−0.523** z = −3.089
(Intercept)	1.617*** z = 18.987	1.858*** z = 14.969	1.858*** z = 14.969
Akaike Inf. Crit.	914.858	906.45	910.594

*p < 0.05, **p < 0.01, ***p < 0.001
[a]Notational Pressure: "None" used as reference category

regression analysis are shown in Table 2. Overall, the model explained 54% of the variance in density. Area per player and number of players each showed a significant inverse relationship with density, with area per player (t = −15.427) showing a slightly greater effect than number of players (t = −13.612). This indicated that as area per player and number of players increased, density on skill involvements was more likely to decrease (Figure 3).

Table 2. Results of the multiple regression analysis estimating the relationship between manipulated environmental constraints (area per player and number of players) and density. Coefficient (*B*) and test statistic (*t*) presented for each variable. *p < 0.01.

	Density	
	B	*t*
Area per Player	−0.003*	−15.427
Number of Players	−0.099*	−13.612
Constant	1.729*	22.969
Adjusted R^2	0.543	

Across all skill involvements the proportion of each level of the pressure constraint represented in the data was; No Pressure = 55%, Physical = 8%, Frontal = 25%, Chase = 12%. To address the third aim, results of the two logistic regression models are shown in Table 1 (Models 2 and 3). Using No Pressure as the reference category, only Physical pressure was shown to have a weak relationship with skill effectiveness (z = −4.315), reducing the likelihood of an effective skill involvement (Model 2). When notational analysis pressure was made a binary variable, a significant inverse relationship with skill effectiveness is shown (Model 3). This indicated that a skill involvement performed under the constraint of pressure, regardless of location, was more likely to be ineffective than effective; however, this association was weak (z = −3.089).

Discussion

The overarching objective of this study was to apply a continuous density metric to represent the constraint of pressure in AF. To achieve this, the first aim examined the relationship between density and skill effectiveness, which revealed that density had a weak, positive association with disposal effectiveness. This was contrary to expectation, as in other spatiotemporal derived methods for pressure measurement, pressure is seen as increasing when distance to a defender decreases (Andrienko et al., 2017; Link et al., 2016). However, unlike in other studies (i.e. Andrienko et al., 2017; Link et al., 2016), the present study's metric is the measurement of displacement for *all* players on the field, relative to the ball carrier. This suggests that this type of measurement presents differently to measurements which only value opposition players within an immediate vicinity. Multiple explanations are offered for this. Firstly, lower density levels around the ball carrier can indicate a wide spread of players across the playing field. This suggests that defending players are well

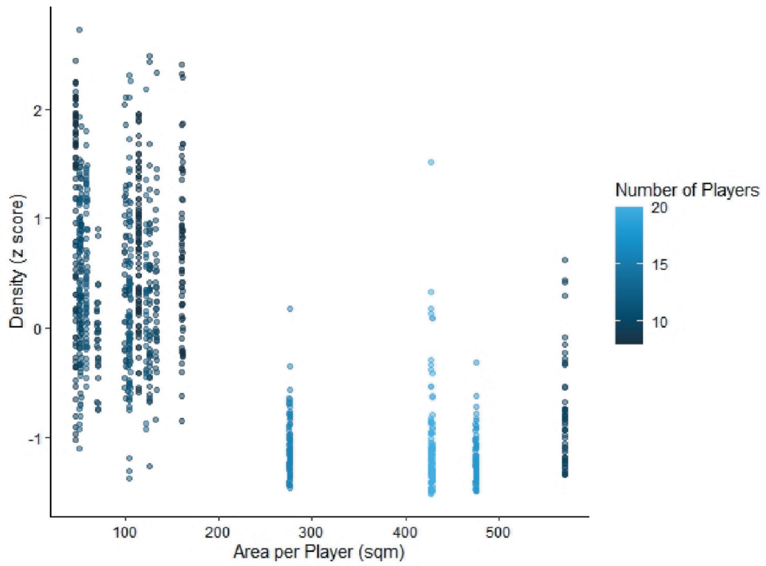


Figure 3. Relationship between environmental constraints (area per player and number of players) and density. Each point represents a skill involvement.

placed to cover large portions of the field, increasing the difficulty on the ball carrier in finding open space around a passing target. Indeed, in AF there is a tendency for players to favour targets with lower density (Spencer et al., 2017). It may also be partially explained by the tactical constraints which shape decision-making by players (Pill, 2014). For example, it is a common tactic among AF players to "draw" opponents closer, creating open spaces around teammates before executing a pass. Therefore, increased density on the ball carrier is likely to be related to lower densities for passing targets, potentially increasing the likelihood for a successful pass. It should also be noted that in the current sample, 83.2% of involvements were effective which represents a higher efficiency than noted during the 2019 competition (71.5%; www.afl.com.au/stats). Thus, these models may infer different results in competition.

Pertaining to the second aim, the relationship between density and environmental constraints showed that both area per player and number of players were inversely associated with density, with area per player having a larger effect than number of players. To date, no work has measured this type of density under constraint manipulation, rather density has been measured as a collective team behaviour through total surface area of players during a training activity (Silva et al., 2015; Timmerman et al., 2017). Findings in the present study support results observed in soccer (Silva et al., 2015), and to some extent, in field hockey (Timmerman et al., 2017). In field hockey, density has been shown to be influenced by environmental constraints, whereby the number of players is more influential than area per player (Timmerman et al., 2017). In AF, pressure on the kicker, as measured through notational analysis, is not solely influenced by manipulating the number of players in a drill (Bonney et al., 2020). This differs to the current study's measure of pressure. However, notational pressure may not be sensitive enough for small constraint manipulations, such as in Bonney et al. (2020), to illicit change. The present study has shown that environmental constraints influence density, relative to the ball carrier, and it is encouraged that practitioners consider this in training design. When designing training, environmental constraints may be strategically manipulated to expose players to skill executions in specific densities, depending on the focus of the session.

The final aim compared pressure measured via notational analysis with the density-derived pressure metric. For the former method, only physical pressure showed a meaningful relationship with skill effectiveness. This was expected, as intuitively, skill performance under physical contact from an opponent would be more challenging than other forms of pressure. This is also in agreement with other work examining kicking in AF (Browne et al., 2019). However, when pressure was dichotomized as "present" (combining all categorizations of pressure) or "absent", a weak negative association was shown, meaning players were more likely to perform an unsuccessful pass when under pressure. This result contradicts the relationship found between density and skill performance. A potential explanation may be in the strict 3 m proximity, within which pressure was measured, through notational analysis. Unlike the density metric, no account is provided of player location beyond this vicinity. While originally hypothesized as a limitation, these results suggest this may be advantageous in understanding skill performance. Providing a value for the underlying distribution of players throughout an entire field may undermine the influence of defenders within the immediate vicinity of the ball carrier. For example, an unsuccessful pass which is measured as under pressure through notational analysis, may also measure low in density, due to the wide spread of players across the rest of the field. It may be concluded that density is not a replacement metric for pressure, as measured through notational analysis, but still contributes to understanding skill performance.

Practically, the results of this study show that density is inversely related to pressure. Consequently, more information may need to be considered in order to explain skill effectiveness more accurately. Specifically, including a measure of pressure or density surrounding targets would be advantageous to better understand the task constraints on skilled behaviour. It is clear that accurate modelling of skill performance requires the measurement of more than a single constraint (Browne et al., 2019; Lucey et al., 2014; Pocock et al., 2018; Vilar et al., 2013). Such multivariate analyses have shown how constraints including pass distance, locomotive velocity and time in possession influence kicking performance in AF (Browne et al., 2019).

The density metric used in this study also contains multiple limitations which should be noted. Notably, measuring player density via kernel density estimation does not reflect player velocity and orientation. Logically, players can apply more pressure to space they are travelling towards (Fernandez & Bornn, 2018). Additionally, whilst density considers the relative locations of opponents, outputting density as a continuous, numerical value does not convey information about the direction of pressure being applied to the passer. Traditionally, pressure is measured categorically in AF by recording the location of pressuring opponents to the player. For example, "chasing" pressure signifies opponents are applying pressure behind the player with possession (Browne et al., 2019; Ireland et al., 2019; Robertson et al., 2019). Future work should address these limitations through utilization of a measure of spatial occupancy that considers player velocity and orientation (e.g. Fernandez & Bornn, 2018; Spencer et al., 2018). Other limitations of the present study include the synchronization of spatiotemporal and skill event data, which carries inherent error due to a reliance on human communication to determine synchronization points, along with timing errors which may occur during event logging of skill data. Additionally, no inter-rater reliability analysis was conducted on skill data. Further, density was limited to a static measurement at the time point of skill executions. While this presents a method which is simple in application, density as a pressure metric may be suited to a measure which occurs over time, such as the seconds leading up to a skill execution or during the entire period of a player's ball possession. It is suggested that future work examine density as it is temporally distributed over such time periods. It is also important to note that density is limited to measurements in a two-dimensional plane; however, AF is a three-dimensional sport where player jumping ability and height may attenuate or increase pressure. Finally, the analysis in this study was conducted on data collected from training sessions. It is likely that disparities between player behaviour in match and training conditions exist, so future work adapting density as a pressure metric should be directed to match play. In AF, it is suggested that match simulations be utilized to achieve this as opposition data is currently restricted during official Australian Football League matches.

Conclusion

This study analysed spatiotemporal data using kernel density estimation to estimate density of players in a continuous manner. This metric was applied in AF training as an alternate measure for the constraint of pressure. Density, relative to the ball-carrier at skill execution, was weakly and positively associated with successful skill performance. These findings contrast with pressure measured through notational analysis. It is suggested that density surrounding the target of a skill execution be considered in future to provide an improved representation of pressure on skill involvements. Increasing the area per player and the number of players in a drill decreases the density on skill involvements. The methods presented here may also be transferred to other sports and be used to contextualize player behaviour in competition and for consideration when designing training environments.

Disclosure of interest

The authors report no conflict of interest.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ORCID

Ben Teune http://orcid.org/0000-0003-4437-535X
Alice J Sweeting http://orcid.org/0000-0002-9185-6773
Carl Woods http://orcid.org/0000-0002-7129-8938
Sam Robertson http://orcid.org/0000-0002-8330-0011

References

Andrienko, G., Andrienko, N., Budziak, G., Dykes, J., Fuchs, G., Von Landesberger, T., & Weber, H. (2017). Visual analysis of pressure in football. *Data Mining and Knowledge Discovery*, *31*(6), 1793–1839. https://doi.org/10.1007/s10618-017-0513-2

Baumeister, R. F., & Showers, C. J. (1986). A review of paradoxical performance effects: Choking under pressure in sports and mental tests. *European Journal of Social Psychology*, *16*(4), 361–383. https://doi.org/10.1002/ejsp.2420160405

Bonney, N., Ball, K., Berry, J., & Larkin, P. (2020). Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. *Journal of Sports Sciences*, *38*(21), 2430–2436. https://doi.org/10.1080/02640414.2020.1787697

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*, *66*, 621–630. https://doi.org/10.1016/j.humov.2019.06.013

Csataljay, G., James, N., Hughes, M., & Dancs, H. (2013). Effects of defensive pressure on basketball shooting performance. *International Journal of Performance Analysis in Sport*, *13*(3), 594–601. https://doi.org/10.1080/24748668.2013.11868673

Davids, K. (2012). Learning design for nonlinear dynamical movement systems. *The Open Sports Sciences Journal*, *5*(1), 1. https://doi.org/10.2174/1875399X01205010009

Davids, K., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach*. Human Kinetics. http://www.humankinetics.com/products/showproduct.cfm?isbn=9780736036863

Eysenck, M. W. (2013). *Anxiety: The Cognitive Perspective*. Psychology Press.

Fernandez, J., & Bornn, L. (2018). Wide open spaces: A statistical technique for measuring space creation in professional soccer. In *Sloan sports analytics conference, 2018*. Boston, MA.

Glazier, P. S. (2017). Towards a grand unified theory of sports performance. *Human Movement Science*, *56*, 139–156. https://doi.org/10.1016/j.humov.2015.08.001

Ireland, D., Dawson, B., Peeling, P., Lester, L., Heasman, J., & Rogalski, B. (2019). Do we train how we play? Investigating skill patterns in Australian football. *Science and Medicine in Football*, *3*(4), 265–274. https://doi.org/10.1080/24733938.2019.1595111

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33* (1), 159–174. JSTOR. https://doi.org/10.2307/2529310

Link, D., Lang, S., & Seidenschwarz, P. (2016). Real time quantification of dangerousity in football using spatiotemporal tracking data. *PLoS ONE*, *11*(12), 12. https://doi.org/10.1371/journal.pone.0168768

Lucey, P., Bialkowski, A., Monfort, M., Carr, P., & Matthews, I. (2014). "Quality vs quantity": Improved shot prediction in soccer using strategic features from spatiotemporal data. In *Proc. 8th annual mit sloan sports analytics conference*, (pp. 1–9). Boston, MA.

McGarry, T. (2009). Applied and theoretical perspectives of performance analysis in sport: Scientific issues and challenges. *International Journal of Performance Analysis in Sport*, *9*(1), 128–140. https://doi.org/10.1080/24748668.2009.11868469

Newell, K. M. (1986). Constraints on the development of coordination. In M. Wade & H. Whiting (Eds.), *Motor Development in children: Aspects of coordination and control* (pp. 341–360). Martinus Nijhoff.

Pill, S. (2014). Informing Game Sense pedagogy with constraints led theory for coaching in Australian football. *Sports Coaching Review*, *3*(1), 46–62. https://doi.org/10.1080/21640629.2014.890778

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup. *European Journal of Sport Science*, *18*(10), 1309–1316. https://doi.org/10.1080/17461391.2018.1486459

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. https://doi.org/10.1080/02640414.2018.1555905

Silva, P., Esteves, P., Correia, V., Davids, K., Araújo, D., & Garganta, J. (2015). Effects of manipulations of player numbers vs. Field dimensions on inter-individual coordination during small-sided games in youth football. *International Journal of Performance Analysis in Sport*, *15*(2), 641–659. https://doi.org/10.1080/24748668.2015.11868821

Simonoff, J. S. (1996). *Smoothing methods in statistics*. Springer-Verlag. https://doi.org/10.1007/978-1-4612-4026-6

Spencer, B., Bedin, T., Farrow, D., & Jackson, K. (2018). A method for evaluating player decision-making in the Australian football league. In *Proceedings of 14th Australasian conference on mathematics and computers in sport*, (pp. 7–12). Sunshine Coast, Australia.

Spencer, B., Morgan, S., Zeleznikow, J., & Robertson, S. (2017). Measuring player density in Australian rules football using gaussian mixture models. *Complex Systems in Sport, International Congress Linking Theory and Practice 5*, 172–174. https://doi.org/10.3389/978-2-88945-310-8

Timmerman, E. A., Farrow, D., & Savelsbergh, G. J. (2017). The effect of manipulating task constraints on game performance in youth field hockey. *International Journal of Sports Science & Coaching*, *12*(5), 588–594. https://doi.org/10.1177/1747954117727659

Timmerman, E. A., Savelsbergh, G. J. P., & Farrow, D. (2019). Creating appropriate training environments to improve technical, decision-making, and physical skills in field hockey. *Research Quarterly for Exercise and Sport*, *90*(2), 180–189. https://doi.org/10.1080/02701367.2019.1571678

Vilar, L., Araújo, D., Davids, K., Correia, V., & Esteves, P. T. (2013). Spatial-temporal constraints on decision-making during shooting performance in the team sport of futsal. *Journal of Sports Sciences*, *31*(8), 840–846. https://doi.org/10.1080/02640414.2012.753155

Woods, C. T., Jarvis, J., & McKeown, I. (2019). Differences between Elite and Semi-Elite Australian Football Conceptualised through the Lens of Ecological Dynamics. *Sports*, *7*(7), 159. https://doi.org/10.3390/sports7070159

Woods, C. T., McKeown, I., Rothwell, M., Araújo, D., Robertson, S., & Davids, K. (2020). Sport practitioners as sport ecology designers: How ecological dynamics has progressively changed perceptions of skill "acquisition" in the sporting habitat. *Frontiers in Psychology*, *11*, 654. https://doi.org/10.3389/fpsyg.2020.00654

VICTORIA UNIVERSITY

THE NEW WAY TO DO UNI

OFFICE FOR RESEARCH TRAINING, QUALITY AND INTEGRITY

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)

Title of Paper/Journal/Book: Application of a continuous pressure metric for Australian Football

https://doi.org/10.1080/02640414.2021.1886416

Surname: Teune First name: Ben

Institute: Institute for Sustainable Industries and Liveabl Candidate's Contribution (%): 70

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 26/07/2021

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] 27/07/2022

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

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

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

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

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

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 storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Bartholomew Spencer	5	Assisted with analysis	[redacted]	14/06/22
Alice Sweeting	5	Assisted with methodology, feedback and revisions		19/07/22
Carl Woods	5	Assisted with feedback and revisions		18/07/22
Mathew Inness	5	Assisted with feedback and revisions		26/06/22
Sam Robertson	10	Assisted with study design, analysis, feedback and revisions		27/07/22

Updated: September 2019

Application of a continuous pressure metric for Australian football

3.1 Abstract

Pressure is an important constraint on sports performance and is typically measured through manual notational analysis. A continuous representation of pressure, along with semi-automated measurement, would serve to improve the efficiency of practice design and analysis, as well as provide additional context to player competition performance. Using spatiotemporal data collected from wearable tracking devices, the present study applied Kernel Density Estimation to estimate the density of players, relative to the ball carrier, at point of skill execution during elite Australian Football training. Two environmental constraints were measured (*area per player* and *number of players*) to determine the relationship between these training design manipulations and density. Density was also compared with existing notational analysis measurements of pressure. Results indicated that a higher density on skills was associated with successful skill executions. The opposite relationship was found between notational analysis pressure measurement and skill effectiveness. A strong inverse relationship was found between environmental constraint manipulation and density, whereby increasing field size and playing number decreased the density on skill involvements. The findings offer insight into the continuous measurement of pressure and encourage practitioners to utilise training design manipulations to influence density as a constraint on skills.

3.2 Introduction

The constraints-led approach (CLA) is a theoretical framework that situates movement as an adaptive property of the performer-environment system (Davids et al., 2008). Constraints act internally and externally to an individual, interacting and changing over time to shape movement and behaviour (Newell, 1986). It is therefore critical, that constraints be measured with sufficient detail and accuracy to gain insight into *how* and *why* particular movements and behaviours emerge (Glazier, 2017; McGarry, 2009). For sport practitioners, the measurement of constraints that shape the behaviour of athletes would likely provide important contextual information for evaluating player behaviour and designing learning environments intended to develop skill (Davids, 2012; Woods, McKeown, Rothwell, et al., 2020). To this end, improving the implementation of the CLA in sport can be achieved through: i) the measurement and consideration of additional constraints, ii) the application of enhanced analytical techniques or, as in the current study, iii) the improved measurement of an existing constraint.

In team sports, a commonly measured constraint is pressure, which is typically defined as the presence of opposition players in a nearby location at the time of skill execution (G. Andrienko et al., 2017). Given this definition, it is often used interchangeably with density (Link et al., 2016). A common method to measure pressure is to subjectively assign levels (e.g. low, medium and high) via notational analysis, according to the distance between an attacker and the nearest defender during skill execution. This has been applied in basketball (Csataljay et al., 2013) and field hockey (Timmerman et al., 2017, 2019). During futsal shots on goal, the distance of defending players to ball trajectory has also been used as an indicator of pressure (Vilar et al., 2013). In soccer, other methods have utilised spatiotemporal data derived from Global Positioning Systems (GPS), such as distance, velocity, and direction of players, to develop numerical measures for pressure (G. Andrienko et al., 2017; Link et al., 2016). The majority of pressure metrics have focused on physical pressure, but other construct definitions of pressure have also been reported in the literature. These include situations incentivising optimal or maximal performance (Baumeister & Showers, 1986), which can manifest through increases in anxiety or emotional responses and thus may negatively impact skill performance (Eysenck, 2013).

In Australian Football (AF), the quantification of pressure has been represented in multiple ways. Types of pressure have been allocated to a skill execution according to the location of defending players, for example, side, frontal, chase or physical (Browne, Sweeting, et al., 2019; Ireland et al., 2019; Robertson et al., 2019b), along with the number of players within a 3 m boundary to the ball carrier (Woods, Jarvis, et al., 2019). Opposition presence around pass receivers has also been recorded as a means of capturing indirect pressure on the passer and direct pressure on the receiver (Browne, Sweeting, et al., 2019; Ireland et al., 2019; Woods, Jarvis, et al., 2019). Some evidence exists to support the validity of pressure being measured in these ways, specifically due to the association with unsuccessful kicks (between 14.6% and 38.5% efficiency) during AF match play (Browne, Sweeting, et al., 2019).

As spatiotemporal data pertaining to players is available in elite AF (with the exclusion of opposition data) there are opportunities to utilise it to improve the sophistication of existing pressure measurements. Thus, a measure of player density was recently developed by applying Gaussian mixture modelling to spatiotemporal datasets during match play (Spencer et al., 2017). This method captured the interaction of all players on the field simultaneously. The work highlighted the changing congestion of players throughout a match, revealing that successful possession chains have large changes in density (Spencer et al., 2017). An adaptation of this type of analysis may provide a valuable metric to improve upon the current measures of pressure by providing a continuous metric. It may also facilitate consideration of the influence of players not within the immediate vicinity of the ball carrier.

The present study seeks to adapt the methodology of Spencer et al. (2017) to use density estimation as a proxy for pressure in AF. The first aim was to determine the extent of the relationship between pressure and the effectiveness of skill involvements. The second aim was to determine the extent to which environmental constraints, as part of training design, influence the pressure on skill execution during training drills. A third aim was to compare pressure derived from density estimation with pressure derived from notational analysis. Establishing these relationships may inform how pressure can be utilised in practice design, while providing additional context to player competition performance.

3.3 Methodology

3.3.1 Participants

Participants were listed male players from a single professional AF club (n = 43, 24.2 ± 3.5 y, 186.8 ± 7.7 cm, 84 ± 7.8 kg). All players provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the relevant University Ethics Committee.

3.3.2 Data collection

Data were collected during the 2020 Australian Football League pre-season. A total of 32 training activities were selected for analysis, consisting of eight different drills and 1014 skill involvements (72% handballs and 28% kicks). Drills that were selected were characterised as small sided games (by the club's coaching staff) and consisted of two opposing teams with equal numbers. Team selection was quasi-randomised by the clubs coaching staff to standardise skill level and player experience. The objectives of each drill were nuanced, they generally required teams to score by kicking a goal or completing a pass into a zone at one end of the field. Further, the drills covered all aspects of AF including ball movement, decision making, offensive and defensive actions. Drills ranged from 46.88 m^2 per player to 570 m^2 per player and the total number of players ranged from eight to 20.

To obtain records of each skill involvement, drills were filmed with a two-dimensional camera from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of the drill at the time of performance. To quantify skill involvements and the surrounding task constraints, notational analysis software was used (Sportscode, version 12.2.10, Hudl). A custom code window was created whereby each skill involvement was recorded live, during the session, according to the method (kick or handball) and the outcome (effective or ineffective). Disposal outcome was defined in accordance with Champion Data (Melbourne, Pty Ltd), the commercial statistics provider for the Australian Football League. A handball or kick less than 40 m was deemed effective if the intended target retained possession of the ball. A kick greater than 40 m was deemed effective if kicked to a 50/50 contest or better for the attacking team. Post training, the Sportscode window was used to attribute additional, notational analysis labels to each skill involvement, according to the type of pressure present. Pressure was categorised into four levels; None, Frontal, Chase and Physical (Robertson et al., 2019b). These levels were also used to determine a binary pressure measurement by combining Frontal, Chase and Physical into 'Present' and using None as 'Absent'. Coders followed club procedure on "what to look for" when performing notational analysis to ensure consistent interpretations. To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic (Landis & Koch, 1977) was used to assess intra-rater reliability of effectiveness and pressure. Agreement was "almost perfect" for effectiveness (0.93) and binary pressure (0.83) and "substantial" for pressure (0.79). All skill involvement data was exported, according to their drill, into a custom Microsoft Excel spreadsheet.

Spatiotemporal data for each player was collected with 10 Hz GPS units (Vector S7, Catapult, Catapult Sports Ltd, Melbourne). Devices were placed in a vest in a custom pouch between the athlete's shoulder blades prior to the session beginning. Players wore the same device during each session to reduce inter-unit error. During the session, splits were created marking the beginning and end of each activity in the manufacturer's software package (*Openfield,* version 2.5.0). To create a reference point to join skill data with spatiotemporal data, a start label was also coded in Sportscode at the start time of each drill. After session completion, raw spatiotemporal data was exported from *Openfield* into Microsoft Excel for each player and for each training activity. To differentiate teammate and opposition locations, using the recorded footage, each player's spatiotemporal data was arbitrarily assigned a team label for each training activity.

To determine player location for each skill involvement, exported spatiotemporal data and skill involvement data were joined according to their timestamp for each training activity. For both datasets, timestamps were adjusted relative to the beginning of each activity. Latitude and longitude for each player was converted to x and y coordinates, in metres, relative to the ball-carrier position which was set at 0,0. Using assigned teams, each player location was labelled as opposition or teammate, relative to the player performing each skill involvement. Kernel density estimation, a method of estimating the probability density function of a dataset via smoothing of individual points, was used to estimate the density of players at each skill involvement (Simonoff, 1996). The kernel function and bandwidth dictate the shape and smoothness of the resultant probability density function, respectively. Density was estimated using Gaussian kernels and the bandwidth was arbitrarily set to 0.00006 for all samples. A visual example of a sample is presented in Figure 3.1. Density was calculated across two groups; all players and opposition players only.

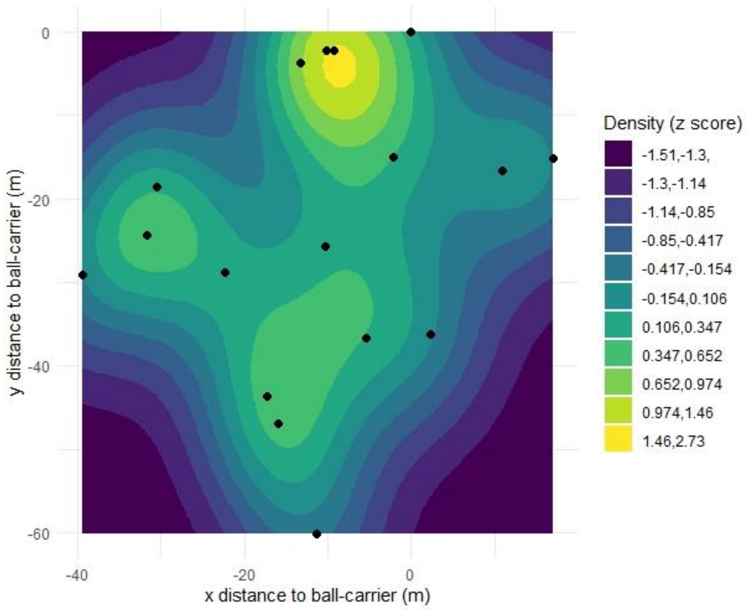


Figure 3.1 Example representation of a single skill involvement. Points represent player positioning relative to the ball-carrier which is at 0,0. Contours and colour represent density (z score), with positive values indicating higher density.

To measure constraint manipulation with respect to training design, two environmental constraints were recorded for each training activity. The constraints selected were *area per player* and total *number of players*, which have shown relationships with player density (Silva et al., 2015; Timmerman et al., 2017). Number of players was defined as the total number of players participating in the drill. The area per player was defined as the total playing area of the field, as designated by markers and manually measured before each activity, divided by the number of players. All constraint manipulations for each training activity were recorded and databased in a custom Microsoft Excel™ spreadsheet.

3.3.3 Statistical Analysis

All statistical analyses were performed in R (R Core Team, 2019) using base R functions. Density estimation scores were normalised to the mean, as *z* scores, for both groups: all players and opposition players. To address the first aim, logistic regression models were constructed to determine the relationship between density and skill effectiveness (effective or ineffective). Visual inspection of the distribution of density revealed no substantial differences when considered as only defending players or all players from both teams combined. Consequentially, the remainder of the analysis considered all players from both teams. Three models were constructed; considering either i) only handballs, ii) only kicks or iii) all skill involvements. To address the second aim, a multiple linear regression model was constructed to determine the relationship between the two manipulated environmental constraints (area per player and number of players) and density. To address the final aim, two logistic regression models were constructed to determine the relationship between i) notational analysis pressure according to location and ii) notational analysis pressure as binary (present or absent) and skill effectiveness (effective or ineffective).

3.4 Results

For the entire dataset, 83.2% of involvements were effective. Density scores for each involvement were a normalised value, where mean = 0 and SD = 1 and where a higher value represents more density on the skill involvement and vice versa. A visualisation of the distribution of density for the entire sample is provided in Figure 3.2. Logistic regression analysis revealed that for handballs only (B = -0.04, z = -0.334) and for kicks only (B = 0.347, z = 0.976), there was a very weak positive relationship between density and effectiveness. Across all skill involvements, logistic regression analysis revealed that density and effectiveness were positively associated (Model 1 in Table 3.1). This indicates when density was higher, it was more likely for an effective disposal to occur, however the association was weak (z = 2.437). Mean density for effective disposals was 0.034 SD and mean density for ineffective disposals was -0.171 SD.

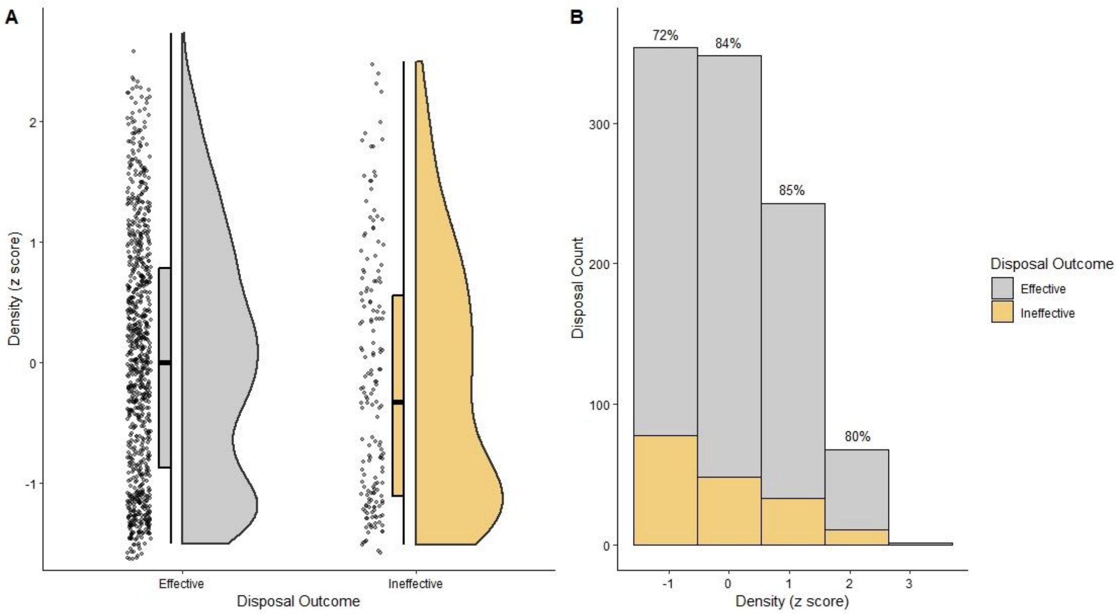


Figure 3.2 Distribution of density for effective and ineffective skill involvements. A: Each dot represents a single skill involvement. Box and whisker plots indicate the median, interquartile range, minimum and maximum values. Half violin plots represent a continuous distribution of density. B: Histogram bars are stacked according to disposal effectiveness with labels above each bin representing disposal effectiveness (%)

Table 3.1 Results of logistic regression models. Model 1 shows the relationship between density and skill effectiveness. Model 2 shows the relationship between each level of pressure measured through notational analysis and skill effectiveness. Model 3 shows the relationship between pressure as a binary notational analysis measurement and skill effectiveness. Coefficient and test statistic (z) presented for each variable.

	Effectiveness		
	Model 1	*Model 2*	*Model 3*
Density	0.212* z = 2.437		
Notational Pressure: Chase[a]		-0.328 z = -1.212	
Notational Pressure: Frontal[a]		-0.366 z = -1.798	
Notational Pressure: Physical[a]		-1.147*** z = -4.315	
Notational Pressure: Binary[a]			-0.523** z = -3.089
(Intercept)	1.617*** z = 18.987	1.858*** z = 14.969	1.858*** z = 14.969
Akaike Inf. Crit.	914.858	906.45	910.594

*p<0.05, **p<0.01, ***p<0.001

[a]Notational Pressure: “None” used as reference category

To address the second aim, 32 training drills were analysed. Descriptive statistics are reported as a mean and standard deviation. The mean number of involvements was 31.7 ± 12.2, the mean disposals per minute was 9.9 ± 4.3, the mean number of players was 11.6 ± 3.5 and the mean area per player was 176.9 m^2 ± 165.2 m^2 per drill. Results of the multiple linear regression analysis are shown in Table 3.2. Overall, the model explained 54% of the variance in density. Area per player and number of players each showed a significant inverse relationship with density, with area per player (t = -15.427) showing a slightly greater effect than number of players (t = -13.612). This indicated that as area per player and number of players increased, density on skill involvements was more likely to decrease (Figure 3.3).

Table 3.2 Results of the multiple regression analysis estimating the relationship between manipulated environmental constraints (area per player and number of players) and density. Coefficient (B) and test statistic (t) presented for each variable. *p<0.01

	Density	
	B	*t*
Area per Player	-0.003*	-15.427
Number of Players	-0.099*	-13.612
Constant	1.729*	22.969
Adjusted R^2	0.543	

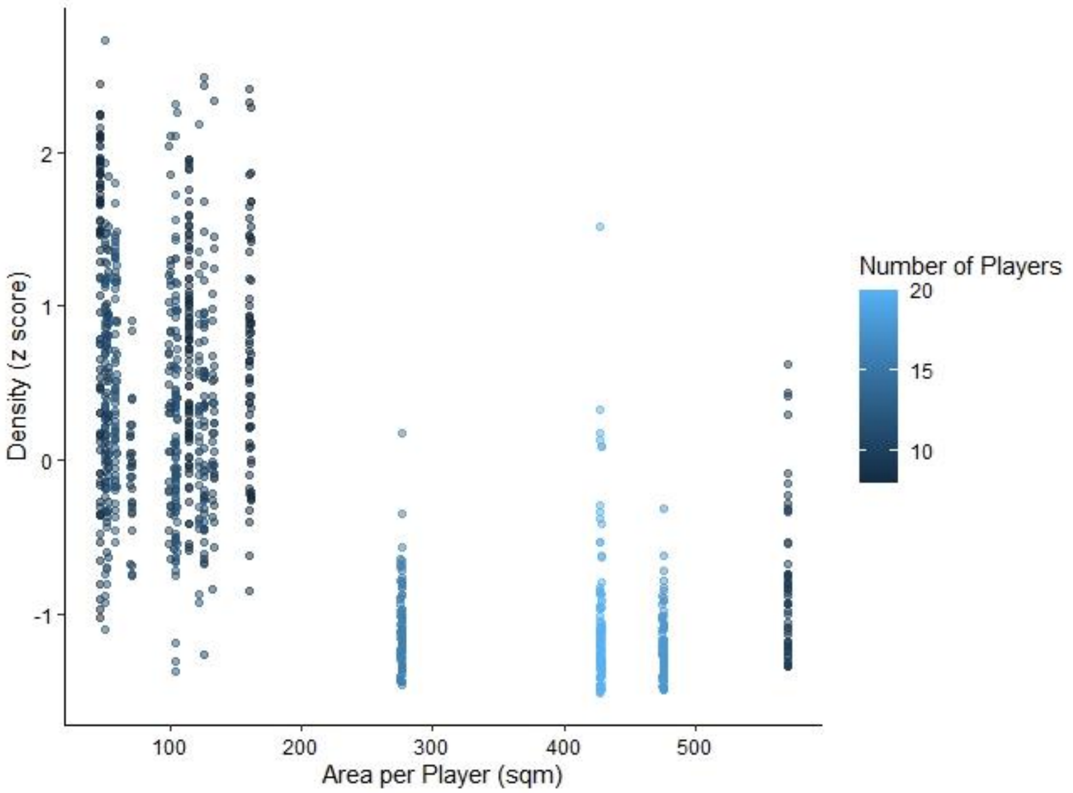


Figure 3.3 Relationship between environmental constraints (area per player and number of players) and density. Each point represents a skill involvement.

Across all skill involvements the proportion of each level of the pressure constraint represented in the data was; No Pressure = 55%, Physical = 8%, Frontal = 25%, Chase = 12%. To address the third aim, results of the two logistic regression models are shown in Table 3.1 (Models 2 and 3). Using No Pressure as the reference category, only Physical pressure was shown to have a weak relationship with skill effectiveness ($z = -4.315$), reducing the likelihood of an effective skill involvement (Model 2). When notational analysis pressure was made a binary variable, a significant inverse relationship with skill effectiveness is shown (Model 3). This indicated that a skill involvement performed under the constraint of pressure, regardless of location, was more likely to be ineffective than effective, however this association was weak ($z = -3.089$).

3.5 Discussion

The overarching objective of this study was to apply a continuous density metric to represent the constraint of pressure in AF. To achieve this, the first aim examined the relationship between density and skill effectiveness, which revealed that density had a weak, positive association with disposal effectiveness. This was contrary to expectation, as in other spatiotemporal derived methods for pressure measurement, pressure is seen as increasing when distance to a defender decreases (G. Andrienko et al., 2017; Link et al., 2016). However, unlike in other studies (i.e., Andrienko et al., 2017; Link et al., 2016), the present study's metric is the measurement of displacement for *all* players on the field, relative to the ball carrier. This suggests that this type of measurement presents differently to measurements which only value opposition players within an immediate vicinity. Multiple explanations are offered for this. Firstly, lower density levels around the ball carrier can indicate a wide spread of players across the playing field. This suggests that defending players are well placed to cover large portions of the field, increasing the difficulty on the ball carrier in finding open space around a passing target. Indeed, in AF there is a tendency for players to favour targets with lower density (Spencer et al., 2017). It may also be partially explained by the tactical constraints which shape decision making by players (Pill, 2014). For example, it is a common tactic among AF players to "draw" opponents closer, creating open spaces around teammates before executing a pass. Therefore, increased density on the ball carrier is likely to be related to lower densities for passing targets, potentially increasing the likelihood for a successful pass. It should also be noted that in the current sample, 83.2% of involvements were effective which represents a higher efficiency than noted during the 2019 competition (71.5%; www.afl.com.au/stats). Thus, these models may infer different results in competition.

Pertaining to the second aim, the relationship between density and environmental constraints showed that both area per player and number of players were inversely associated with density, with area per player having a larger effect than number of players. To date, no work has measured this type of density under constraint manipulation, rather density has been measured as a collective team behaviour through total surface area of players during a training activity (Silva et al., 2015; Timmerman et al., 2017). Findings in the present study support results observed in soccer (Silva et al., 2015), and to some extent, in field hockey (Timmerman et al., 2017). In field hockey, density has been shown to be influenced by environmental constraints, whereby the number of players is more influential than area per player (Timmerman et al., 2017). In AF, pressure on the kicker, as measured through notational analysis, is not solely influenced by manipulating the number of players in a drill (Bonney et al., 2020). This differs to the current study's measure of pressure. However, notational pressure may not be sensitive enough for small constraint manipulations, such as in Bonney et al. (2020), to illicit change. The present study has shown that environmental constraints influence density, relative to the ball carrier, and it is encouraged that practitioners consider this in training design. When designing training, environmental constraints may be strategically manipulated to expose players to skill executions in specific densities, depending on the focus of the session.

The final aim compared pressure measured via notational analysis with the density-derived pressure metric. For the former method, only physical pressure showed a meaningful relationship with skill effectiveness. This was expected, as intuitively, skill performance under physical contact from an opponent would be more challenging than other forms of pressure. This is also in agreement with other work examining kicking in AF (Browne, Sweeting, et al., 2019). However, when pressure was dichotomised as "present" (combining all categorisations of pressure) or "absent", a weak negative association was shown, meaning players were more likely to perform an unsuccessful pass when under pressure. This result contradicts the relationship found between density and skill performance. A potential explanation may be in the strict 3 m proximity, within which pressure was measured, through notational analysis. Unlike the density metric, no account is provided of player location beyond this vicinity. While originally hypothesised as a limitation, these results suggest this may be advantageous in understanding skill performance. Providing a value for the underlying distribution of players throughout an entire field may undermine the influence of defenders within the immediate vicinity of the ball carrier. For example, an unsuccessful pass which is measured as under pressure through notational analysis, may also measure low in density, due to the wide spread of players across the rest of the field. It may be concluded that density is not a replacement metric for pressure, as measured through notational analysis, but still contributes to understanding skill performance.

Practically, the results of this study show that density is inversely related to pressure. Consequently, more information may need to be considered in order to explain skill effectiveness more accurately. Specifically, including a measure of pressure or density surrounding targets would be advantageous to better understand the task constraints on skilled behaviour. It is clear that accurate modelling of skill performance requires the measurement of more than a single constraint (Browne, Sweeting, et al., 2019; Lucey et al., 2014; Pocock et al., 2018; Vilar et al., 2013). Such multivariate analyses have shown how constraints including pass distance, locomotive velocity and time in possession influence kicking performance in AF (Browne, Sweeting, et al., 2019).

The density metric used in this study also contains multiple limitations which should be noted. Notably, measuring player density via kernel density estimation does not reflect player velocity and orientation. Logically, players can apply more pressure to space they are travelling towards (Fernandez & Bornn, 2018). Additionally, whilst density considers the relative locations of opponents, outputting density as a continuous, numerical value does not convey information about the direction of pressure being applied to the passer. Traditionally, pressure is measured categorically in AF by recording the location of pressuring opponents to the player. For example, ‘chasing’ pressure signifies opponents are applying pressure behind the player with possession (Browne, Sweeting, et al., 2019; Ireland et al., 2019; Robertson et al., 2019b). Future work should address these limitations through utilisation of a measure of spatial occupancy that considers player velocity and orientation (e.g., Fernandez & Bornn, 2018; Spencer et al., 2018). Other limitations of the present study include the synchronisation of spatiotemporal and skill event data, which carries inherent error due to a reliance on human communication to determine synchronisation points, along with timing errors which may occur during event logging of skill data. Additionally, no inter-rater reliability analysis was conducted on skill data. Further, density was limited to a static measurement at the time point of skill executions. While this presents a method which is simple in application, density as a pressure metric may be suited to a measure which occurs over time, such as the seconds leading up to a skill execution or during the entire period of a player's ball possession. It is suggested that future work examine density as it is temporally distributed over such time periods. It is also important to note that density is limited to measurements in a two-dimensional plane however, AF is a three-dimensional sport where player jumping ability and height may attenuate or increase pressure. Finally, the analysis in this study was conducted on data collected from training sessions. It is likely that disparities between player behaviour in match and training conditions exist, so future work adapting density as a pressure metric should be directed to match play. In AF, it is suggested that match simulations be utilised to achieve this as opposition data is currently restricted during official Australian Football League matches.

3.6 Conclusion

This study analysed spatiotemporal data using kernel density estimation to estimate density of players in a continuous manner. This metric was applied in AF training as an alternate measure for the constraint of pressure. Density, relative to the ball-carrier at skill execution, was weakly and positively associated with successful skill performance. These findings contrast with pressure measured through notational analysis. It is suggested that density surrounding the target of a skill execution be considered in future to provide an improved representation of pressure on skill involvements. Increasing the area per player and the number of players in a drill decreases the density on skill involvements. The methods presented here may also be transferred to other sports and be used to contextualise player behaviour in competition and for consideration when designing training environments.

CHAPTER FOUR – STUDY II

Chapter Overview

Chapter Four is the second of five studies contained in this thesis. Following the specific analysis of a single constraint in chapter three, this chapter moves to investigate training activities more broadly, examining the influence of multiple interacting constraints on player behaviour. Specifically, this study investigates how association rules machine learning algorithm may be applied AF to inform the design of training activities.

The content of this chapter is an accepted manuscript of an article published by Taylor & Francis in the European Journal of Sport Sciences on 26th July 2021, available at: http://www.tandfonline.com/10.1080/17461391.2021.1958011

EUROPEAN JOURNAL OF SPORT SCIENCE
https://doi.org/10.1080/17461391.2021.1958011

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

The influence of environmental and task constraint interaction on skilled behaviour in Australian Football

Ben Teune [a,b], Carl Woods [a], Alice Sweeting [a,b], Mathew Inness[a,b] and Sam Robertson [a]

[a]Institute for Health and Sport (iHeS), Victoria University, Melbourne, Australia; [b]Western Bulldogs, Melbourne, Australia

ABSTRACT

The design of sports practice environments can be informed through data collected and analysed according to principles of the constraints-led approach. In this study, three manipulated environmental (area per player, number of players and team outnumber) and two task (activity objective and disposal limitations) constraints were measured during professional Australian Football training activities ($n = 112$) to determine their relationship with skilled behaviour. Linear regression modelling of the five manipulated constraints explained 68% of the variance in disposal frequency but only 22% in skill efficiency. Activities with scoring objectives, limited to kicking or which permitted all disposals, reduced the disposal frequency per player. Activities which permitted all disposals were also weakly, negatively associated with skill efficiency. A Classification Based on Association analysis measured the interaction between manipulated constraints and their relationships with possession time and pressure. When compared to the null model, the analysis improved pressure classification accuracy by 5.9% and did not improve possession time classification accuracy. This indicates skills were often performed under varying spatial and temporal constraints during many of the training activities. This study presents multivariate analytical methods which consider constraint interaction, enhancing how practitioners can evaluate and inform training design in sport.

KEYWORDS
Team sport; coaching; training; performance analysis; constraints-led approach

Introduction

Designing practice environments that support athlete learning and improve performance is an important consideration for sports practitioners (Davids, 2012). A framework commonly used to guide the design of such practice environments is the constraints-led approach (Newell, 1986). In this framework, constraints are viewed as boundaries, occurring over varying timescales, that shape emergent behaviour of individuals and groups (Newell, Liu, & Mayer-Kress, 2001). Constraints can be categorised into task, performer and environmental classes (Newell, 1986). In sport, task constraints relate to the intent of the activity, inclusive of the rules or equipment used. Performer constraints pertain to the individual, including their anthropometric attributes and physiological qualities. Environmental constraints typically include features external to the performer, and may include the weather, lighting or field dimensions (Newell, 1986).

By identifying constraints which are most influential on athlete behaviours during competition, practitioners can carefully design them into practice tasks – amplifying or dampening them to help channel or guide certain behaviours during training (Renshaw, Chow, Davids, & Hammond, 2010). These manipulations should encourage problem-solving and facilitate athlete-environment interactions (Woods et al., 2020). Evaluation of these manipulations can then determine whether the desired behavioural outcome is being functionally achieved. Athlete behaviour responses to the intentional manipulation of constraints in practice design have been examined across a variety of sports. For example, manipulations of field size can be inversely related to the frequency of some team-sport actions, such as interceptions, shots on goal or tackles (Casamichana & Castellano, 2010; Fleay, Joyce, Banyard, & Woods, 2018). Decreasing the number of players in a practice task can increase the number of actions performed per player, such as (un)successful passes or dribbles (Sarmento et al., 2018; Timmerman, Savelsbergh, & Farrow, 2019), while creating a team imbalance (i.e. 6 vs. 5) may increase the proportion of successful passes completed in Australian Football (AF) small side games (Bonney, Ball, Berry, & Larkin, 2020).

CONTACT Ben Teune benteune@outlook.com

An ongoing methodological challenge in the modelling of athlete behaviour during training and competition is that constraints do not function in isolation, but interact dynamically and often non-linearly (Newell, 1986). For example, in youth football, playing space and the distance between players may be influenced by the interaction of field dimensions (environmental constraint), skill level (performer constraint) and playing numbers (task constraint) (Silva et al., 2014, 2015). In field hockey, both field characteristics and playing numbers influenced action frequencies – increasing or decreasing them based on the emergent time and task goals (Timmerman et al., 2019). Considering how constraints interact may provide practitioners with greater context, potentially improving their understanding on how they can design training environments to facilitate athlete learning. Therefore, measuring multiple constraints and utilising analytical methods which account for these interactions is recommended (Browne, Sweeting, Davids, & Robertson, 2019; Robertson, Spencer, Back, & Farrow, 2019). Practically, constraint measurement is typically limited by resources and costs, meaning no model can be fully complete. However, as the feasibility of capturing constraints in the field is increased due to technological improvements, furthering this methodology presents a worthwhile exercise. Rule induction represents one such analysis approach that is fit for the purpose of this exercise. Specifically, it focusses on identifying the most commonly occurring and influential patterns in data, an approach that closely matches the human method of heuristics (Agrawal, Mannila, Srikant, Toivonen, & Verkamo, 1996). In a scenario of growing data volume, this encourages the user to focus on only those non-linear interactions which are most important in terms of modelling a phenomenon of interest.

A rule induction method for analysing constraint interaction was recently utilised to evaluate kicks during AF match play (Robertson et al., 2019) and has been contrasted with univariate analysis (Browne et al., 2019). For example, Browne et al. (2019) noted that when compared with univariate analysis, rule induction provided a more comprehensive insight into the kicking performance of Australian footballers. This was manifest in kicks under physical pressure being more accurate when coupled with task constraints of longer possession time and kicks to targets that were unmarked or unopposed. Using similar analysis, the current study aims to ascertain the strength of relationship between task and environmental constraints manipulated as part of the training design, and (a) their effects on the frequency and effectiveness of skill involvements, and (b) the prevalence of constraints on skill involvements.

Methodology

Participants

Participants were listed players ($n = 43$; 24.2 ± 3.5 y; 186.8 ± 7.7 cm; 84 ± 7.8 kg) from one professional AF club. All participants provided written informed consent and were injury free at the time of participation in the selected activities. Ethical approval was obtained from the University Ethics Committee.

Data collection

Data collection occurred during the club's 2020 Australian Football League pre-season training period. Training activities ($n = 112$) with environmental and task constraint manipulations were captured, consisting of 20 different activity types and 3907 skill involvements. To obtain information on training design, five manipulated constraints were used: three environmental and two task constraints (Figure 1). The constraints selected were based on the literature (Bonney et al., 2020; Timmerman et al., 2019) and consultation with expert AF coaches at the club. For each drill, the total number of players and team outnumber were recorded, with the field dimensions manually recorded using a measuring wheel. Activity objective (i.e. possession or scoring) and disposal limitation (i.e. handballs, kicking or all disposals) were additionally recorded.

To record each skill involvement, activities were filmed at 25 Hz with a two-dimensional camera (Canon XA25/Canon XA20) from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of drill at the time of performance. To quantify skill involvements and the surrounding task constraints,

Figure 1. Manipulated environmental and task constraints (left) and constraints on skill involvements (right) with associated levels where appropriate.

notational analysis software was used (Sportscode, version 12.2.10, Hudl). A customised code window was created whereby each skill involvement was recorded according to "type" (kick or handball) and "outcome" (effective or ineffective). The effectiveness of the skill involvement was defined in accordance with Champion Data (Melbourne, Pty Ltd), with a handball or kick <40 m deemed effective, if the intended target retained ball possession. A kick >40 m was deemed effective if kicked to a 50/50 contest or outnumber to the advantage of the attacking team. Effectiveness was represented as skill efficiency (%), defined as the number of effective skill involvements in each drill relative to the total number of skill involvements. Disposal frequency was represented as the total number of disposals relative to the duration of the activity and the number of players in the activity (disposals/min/player). To capture the task constraints on each skill involvement, the Sportscode window was used to add additional labels, defined through consultation with club coaches and adapted from the literature (Robertson et al., 2019). As shown in Figure 1, time in possession was discretised into two groups; <2 s or ≥2 s and pressure was categorised as present or absent. Pressure was defined by the presence of an opposition player within 3 m of the passer at moment of ball disposal (Robertson et al., 2019). Efficiency, disposal frequency, time in possession and pressure were then exported, according to their drill, into a custom Microsoft Excel spreadsheet. Constraint manipulation data and skill involvement data were then joined according to the training activity, forming a single database.

To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic was used to assess intra-rater reliability of each variable (Landis & Koch, 1977). Agreement was "almost perfect" for the time in possession (0.83) and effectiveness (0.93) and "substantial" for pressure (0.79).

Statistical analysis

All statistical analysis occurred in R (R Core Team, 2019). To address the first aim, two multiple linear regression models were used to determine the relationship between the manipulated environmental constraints (area per player, number of players and team outnumber) and task constraints (drill objective and disposal limitations) and their effect on (a) disposal frequency and (b) skill efficiency.

To determine the influence of task and environmental constraints on the time in possession and pressure of each skill involvement, a Classification Based on Association (Liu, Hsu, & Ma, 1998) approach was utilised. The Classification Based on Association (Liu et al., 1998) creates a model to predict the class of a variable based upon association rules mined in a dataset. A default rule is also generated in the model for which a class prediction is made for items which do not meet the mined rules. Each rule is presented with associated support and confidence levels. Support (%) is a measure for how frequently a rule appeared in the database and confidence (%) measures the frequency of a class, given the associated rule.

The *ArulesCBA* package (Hahsler & Johnson, 2020) was used to run the *CBA* algorithm (Liu et al., 1998) to construct two models; classification of time in possession and pressure. A random sample of 70% (2734 skill involvements) of the dataset was selected for classifier training. To prepare the data for analysis, discretisation of the area per player, number of players and team outnumber variables was conducted through the *ArulesCBA* package which used the minimum description length principle to bin data. The breaks for each discretisation in the time in possession model were: area per player; 93, 249, 276, 267, 590, number of players; 15 and team outnumber; 1, 4.5. The breaks for each discretisation in the pressure model were: area per player; 131, 235, 263, 276, 451, 522, number of players; 9 and team outnumber; 4.5. Parameters for both constructed models were set with a minimum support of 0.03 and minimum confidence of 0.5. Both models were required to use rules with five items representing each of the manipulated constraints and pruning occurred with the M1 method. The models constructed from the training data were then used to predict the classification of time in possession and pressure on the remaining 30% (1173 skill involvements) of the dataset. Classification accuracy of the two models were evaluated with a confusion matrix.

Results

All descriptive statistics are reported as a mean and standard deviation. Across all activities, the mean area per player was 338 ± 269 m^2, mean number of players was 12 ± 4.3 and mean team outnumber was 0.7 ± 1.2. Within the dataset, 40% of activities were limited to handballs, 12% were limited to kicks and 48% permitted all disposals. Activities with possession-based objectives comprised 15% of the dataset whilst activities with scoring-based objectives were 85%. Mean skill efficiency across all activities was 80.9 ± 9.13% and mean disposals per player per minute was 0.81 ± 0.38.

As displayed in Table 1, the linear regression models showed the manipulated environmental and task constraints had a stronger relationship with disposal

Table 1. Results of multiple linear regression analysis between manipulated environmental and task constraints and disposal frequency (Model 1) and skill efficiency (Model 2).

	Model 1 Disposal frequency			Model 2 Skill efficiency		
	B	SE	*t*	*B*	SE	*t*
(Intercept)	1.880 ***	0.145	12.954	93.596 ***	5.508	16.992
Area per player (m^2)	0.0001	0.0001	1.079	0.007	0.006	1.123
Number of players	−0.014 *	0.006	−2.436	−0.163	0.218	−0.748
Team outnumber	0.014	0.021	0.646	1.373	0.815	1.685
Activity objective: scoring[a]	−0.632 ***	0.150	−4.220	−7.435	5.682	−1.309
Disposal limits: kicking[b]	−0.945 ***	0.171	−5.536	−14.753 *	6.480	−2.277
Disposal limits: no limits[b]	−0.707 ***	0.095	−7.475	−12.582 ***	3.593	−3.502
Adjusted R^2	0.679			0.216		

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.
B = coefficient, SE = standard error of the coefficient, *t* = test statistic.
[a]Activity objective: possession used as reference category.
[b]Disposal limits: handballs used as reference category.

frequency (Adjusted $R^2 = 0.679$) than skill efficiency (Adjusted $R^2 = 0.216$). The relationship between manipulated constraints and disposal frequency and skill efficiency is visualised in Figure 2. Activities permitting all disposals ($t = -7.475$), limited to kicking only ($t = -5.536$) or with a scoring objective ($t = -4.220$) had strong negative relationships with disposal frequency. Area per player ($t = 1.079$) and team outnumber ($t = 0.646$) had weak positive associations with disposal frequency (Table 1). Activities permitting all disposals ($t = -3.502$) also had a strong negative relationship with skill efficiency. Area per player ($t = 1.123$), the number of players ($t = -0.748$), team outnumber ($t = 1.685$) and scoring objectives ($t = -1.309$) each had weak associations with skill efficiency (Table 1).

For the time in possession constraint, the proportion of each class was: <2 s = 66% and ≥2 s = 34%. For the pressure constraint, each class was: None = 58% and Pressure = 42%. The time in possession classifier resulted in seven rules, and the pressure classifier five, as displayed in Table 2. Excluding the default rule, which makes a prediction for items which do not meet the rules produced in the model, rules produced to classify time in possession ranged from 60% to 95% confidence. Rules to classify pressure ranged from 74% to 84% confidence. The confusion matrix revealed the time in possession and pressure classifiers had accuracies of 66% and 63.9%, respectively. Using the majority constraint class in the dataset (<2 s = 66%) as a threshold, the time in possession classifier did not improve class prediction accuracy. However, the pressure classifier slightly improved class prediction accuracy (+5.9%), compared to the majority constraint class (None = 58%).

Discussion

This study demonstrated how environmental and task constraint manipulations can be evaluated to determine their influence on skilled behaviour in AF. The constraints manipulated in the current study were more influential on disposal frequency than skill efficiency, with disposal frequency more predictable than skill efficiency. Further, using an analysis approach such as Classification Based on Association highlighted the non-linearity of constraint interaction. The analysis only slightly improved, upon the majority class threshold, the classification accuracy of pressure and did not improve possession time classification accuracy. This demonstrated the tendency for activities to comprise skill involvements in different classes of constraints, indicating variable participant behaviour. This means participants were exposed to skill involvements in a range of performance contexts. Measurement of athlete skill variability can assist practitioners to evaluate if training aims are being achieved.

Linear regression modelling was used to determine the relationship between manipulated task and environmental constraints and disposal frequency, explaining 67.9% of the variance in disposal frequency. This result highlights the capability of models to predict, with some certainty, the disposal frequency of players in activities. This information could be beneficial for practitioners when estimating skill volumes, which has application for planning training designs (Farrow & Robertson, 2017) and prescribing training loads for rehabilitating athletes. A caveat to this application is that behaviour will still vary between players, manifest through things like playing position, ability, age (Almeida, Duarte, Volossovitch, & Ferreira, 2016), height (Cordovil et al., 2009), and/or previous experience (Pocock, Bezodis, Davids, & North, 2018), which will require consideration. This caveat serves as an important avenue for future work to extend on the current findings. Area per player did not influence disposal frequency, which is in agreement with similar work in AF

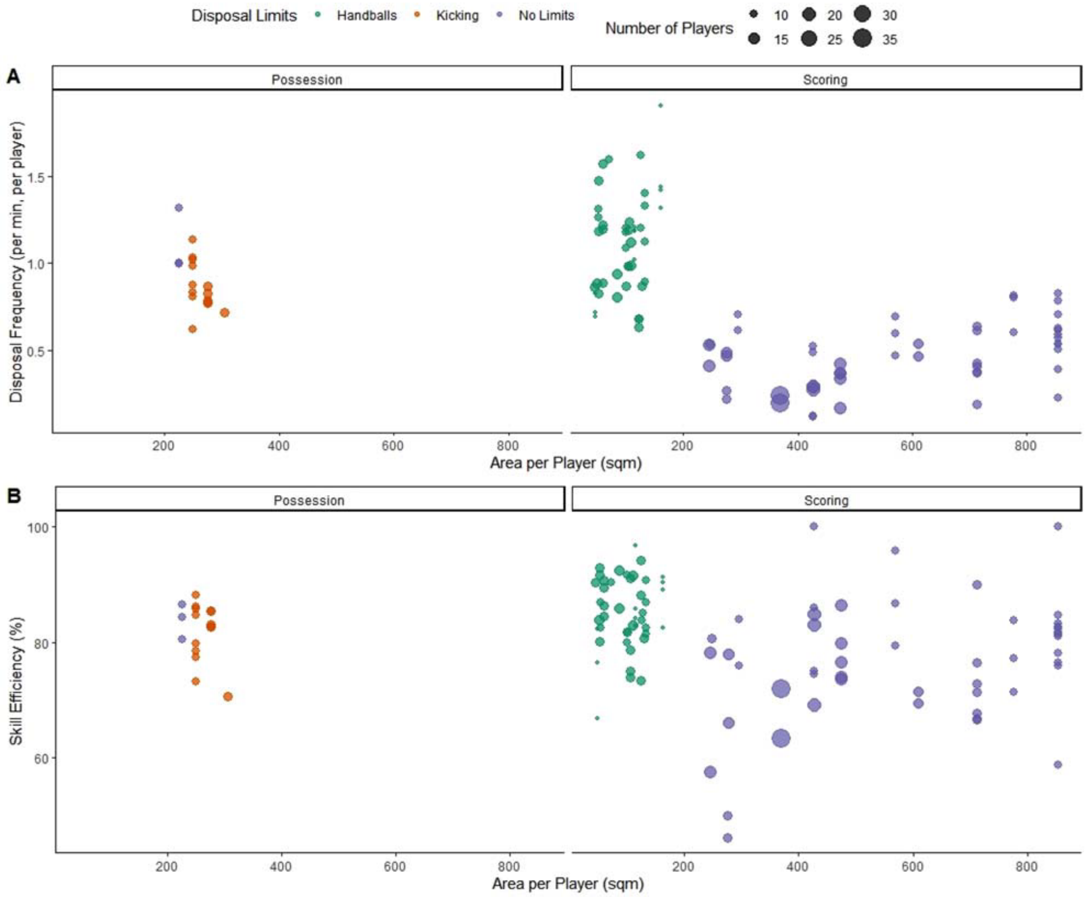


Figure 2. Relationship between manipulated environmental (area per player and number of players) and task (activity objective and disposal limitations) constraints and disposal frequency (A) and skill efficiency (B). Disposal frequency is reported as disposals, per min, per player and skill efficiency is reported as the number of effective involvements relative to total involvements (%). Each point represents a single training activity.

(Fleay et al., 2018) and other team-sports (Casamichana & Castellano, 2010; Kelly & Drust, 2009). However, area per player can influence other action frequencies not measured in the current study, such as tackles and interceptions (Casamichana & Castellano, 2010; Fleay et al., 2018; Kelly & Drust, 2009).

Table 2. Rulesets for the time in possession and pressure classification based on association models.

Model	Area per player (m^2)	Number of players	Team outnumber	Activity objective	Disposal limits	Constraint class	Support (%)	Confidence (%)
Time in possession	248–263	0–15	1–4.5	Possession	Kicking	<2 sec	9.9	95.4
	92.9–248	0–15	1–4.5	Possession	All disposals	<2 sec	3.5	84.4
	0–92.9	0–15	0–1	Scoring	Handballs	<2 sec	10.6	83.4
	263–276	0–15	1–4.5	Possession	Kicking	<2 sec	4.6	72.1
	92.9–248	0–15	0–1	Scoring	Handballs	<2 sec	14.9	62.5
	276–590	15-Inf	0–1	Scoring	All disposals	>2 sec	8.8	60.3
						<2 sec	65.8	65.8
Pressure	235–263	9-Inf	0–4.5	Possession	Kicking	None	8.7	84.1
	523-Inf	9-Inf	0–4.5	Scoring	All disposals	None	13.1	76.4
	131–235	9-Inf	0–4.5	Scoring	Handballs	Pressure	3.1	75.8
	276–451	9-Inf	0–4.5	Scoring	All disposals	None	8.7	73.6
						Pressure	42.4	42.4

The time in possession and pressure class is predicted based on the five associated manipulated constraints with support and confidence provided for each rule. Rules are ordered by confidence with a default rule provided for each model.

Activities with a scoring objective, limited to kicking only or which permitted all disposals, were most associated with decreasing the mean disposal frequency per player. Accordingly, permitting kicks to occur within a drill, in addition or exclusion to handballs, decreased disposal frequency. Execution of the kicking action takes longer than the handball, however this result may also be partially explained by the rules of AF. In AF, catching a kicked pass over 15 m (a "mark") results in a stoppage of play which acts as a task constraint on behaviour. When kicking is permitted, players may be exploiting this task constraint to afford themselves additional time for decision making. This behaviour slows the play of the drill, reducing the volume of disposals accrued. AF practitioners may want to consider this when determining the length of time for activities to provide players enough time to accrue desired action opportunities. More generally, it is advised that sport practitioners consider how task constraints may increase or decrease the frequency of action opportunities provided to their athletes.

Manipulating the number of players in the drill was also shown to influence disposal frequency, albeit to a lesser extent than disposal limitations or drill objective. This result is similar to research in field hockey (Timmerman et al., 2019), but dissimilar to other work in AF (Bonney et al., 2020). Results from the present study may be due to the larger manipulations of playing number. Importantly, reducing playing number increases opportunities for players to explore possible movement solutions (Davids, Araújo, Correia, & Vilar, 2013), while offering a simple and effective constraint manipulation available for coaches.

Modelling of skill efficiency was not as accurate as for disposal frequency, explaining only 26% of the variation. Similar results were observed when modelling rugby place kick performance during match play, explaining 28% variance (Pocock et al., 2018). Additional, or alternative, constraints may be required to predict skill efficiency more accurately. Skill efficiency, or relative frequency of skill errors, may be indicative of how challenging a training drill is for players (Farrow & Robertson, 2017). This is an important consideration for training design as an appropriately challenging environment may promote exploration for new movement solutions (Davids et al., 2013; Renshaw et al., 2010). It should be noted that the 2019 competition average disposal efficiency was 71.5% (obtained from https://www.afl.com.au/stats) compared to 80.9% in the present study. This may mean that the constraints manipulated during training presented a less challenging environment to players.

In the present study, activities which permitted all disposals or were limited to kicking only were most associated with reducing skill efficiency. This may indicate that kicking was a more difficult skill to execute than handballing. Similarly, in soccer, the success of passes and interceptions during small side games has been influenced by manipulating the task constraint of scoring mode (Almeida et al., 2016). Manipulating the team outnumber or area per player did not influence skill efficiency in the present study, which conflicts with other small sided game research in AF (Bonney et al., 2020) and field hockey (Timmerman, Farrow, & Savelsbergh, 2017). These results may be explained by the higher skill level of the current study's participants who can express greater skill proficiency adapted across a variety of conditions.

A multivariate analysis is more appropriate for understanding skilled behaviour (Browne et al., 2019; Robertson et al., 2019). In the present study, a Classification Based on Association approach determined the interactions between manipulated task and environmental constraints and their influence on the possession time and pressure on skill involvements. The variable rulesets, and associated confidence levels produced in the two models demonstrate the non-linearity of environmental and task constraint interaction during training. The complexity of constraint interaction is similarly exemplified during match play in other AF work (Browne et al., 2019, 2020). It is suggested that coaches seeking to apply principles of the constraints-led approach should measure and analyse constraint manipulations in a multivariate manner to appropriately contextualise player behaviour during training. Capturing detail in this way can provide further insight into *how* and *why* certain behaviours emerge (Glazier, 2017).

Each rule presented in the models demonstrate the adaptive behaviour of players within training activities. Accordingly, this highlights how practitioners can facilitate skill development through the design of training environments (Woods et al., 2020). Practically, Classification Based on Association can be utilised to assist coaches in achieving this by informing training design. For example, a coach may seek to develop player skill by increasing the temporal demands on players when passing. The rules presented in the possession time classifier (Table 2) can inform the coach of the relevant constraint manipulations which achieve this. For example, the top row of Table 2 shows the set of constraint manipulations which maximise the frequency of skill involvements with <2 s possession time (95%). Thus, using Classification Based on Association, a practitioner could evaluate the behaviour of players within training activities and use this to inform future drill prescription.

Neither classification model was able to substantially improve, upon the majority class threshold, the accuracy of predicting time in possession or pressure. Accordingly, this indicates that many of the activities in the dataset did not constrain participants to a high frequency of skill involvements in a single class of time in possession or pressure. This demonstrates the inherent variability of AF small side games which can promote movement performance in a range of contexts (Davids et al., 2013). These results may be an example of training which encourages athletes to explore different movement solutions to achieve tasks (Chow, 2013). Thus, evaluating the accuracy of predictive models may help practitioners measure the functional variability in training, where low prediction capability is not always viewed as a negative outcome.

Importantly, it should be noted that the proportion of constraint classes and manipulations across the dataset are representative of the participant coaching and playing styles. Team strategy and coaching philosophies will likely influence the focus of training sessions, guiding the design and selection of training activities. Results of the current study are population specific and practitioners are encouraged to utilise a similar methodology, as presented here, to inform their own training. Through a multivariate analysis, such as Classification Based on Association, practitioners can further contextualise their athlete's behaviour, evaluating and informing their own constraint manipulations in the field.

Given the applied nature of this study, there were some limitations which should be stated. Skill involvement data were collected in the field where constraint manipulation was not systematic but designed by coaches as desired for any given session. The representation of some constraint manipulations and constraint classes in the dataset are unequal, potentially influencing some results. Future work should be directed to collecting additional constraints to include in analyses to aide in constructing more sophisticated models. Environmental constraints such as weather or performer constraints such as age or playing experience may play an important role in influencing skilled behaviour during training. The inclusion of coach experiential knowledge is recommended to identify these key constraints (Greenwood, Davids, & Renshaw, 2012; Pocock, Bezodis, Wadey, & North, 2020).

Conclusion

This study examined the relationship between environmental and task constraint manipulations with skilled behaviour in elite AF. Constraint manipulations explained more variance in disposal frequency than skill efficiency. Designing activities that have a scoring objective and permitted kicking tended to reduce the disposal frequency of players. Designing activities which permitted any disposal method were most associated with a decrease in skill efficiency, creating a more challenging environment for players. A Classification Based on Association approach highlighted the variability of training activities and demonstrated how multivariate analysis can be used to determine constraint interaction, including influencing possession time and pressure on skill involvements. To enhance athlete skill development, practitioners are encouraged to measure interacting constraint manipulations, using similar multivariate analysis, to evaluate and inform their own training design.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Ben Teune http://orcid.org/0000-0003-4437-535X
Carl Woods http://orcid.org/0000-0002-7129-8938
Alice Sweeting http://orcid.org/0000-0002-9185-6773
Sam Robertson http://orcid.org/0000-0002-8330-0011

References

Agrawal, R., Mannila, H., Srikant, R., Toivonen, H., & Verkamo, A. I. (1996). Fast discovery of association rules. *Advances in Knowledge Discovery and Data Mining*, *12*(1), 307–328.

Almeida, C. H., Duarte, R., Volossovitch, A., & Ferreira, A. P. (2016). Scoring mode and age-related effects on youth soccer teams' defensive performance during small-sided games. *Journal of Sports Sciences*, *34*(14), 1355–1362. doi:10.1080/02640414.2016.1150602

Bonney, N., Ball, K., Berry, J., & Larkin, P. (2020). Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. *Journal of Sports Sciences*, *30*(21), 2430–2436.

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*, *66*, 621–630. doi:10.1016/j.humov.2019.06.013

Browne, P. R., Woods, C. T., Sweeting, A. J., & Robertson, S. (2020). Applications of a working framework for the measurement of representative learning design in Australian football. *PLoS One*, *15*(11), e0242336. doi:10.1371/journal.pone.0242336

Casamichana, D., & Castellano, J. (2010). Time–motion, heart rate, perceptual and motor behaviour demands in small-sides soccer games: Effects of pitch size. *Journal of Sports*

Sciences, *28*(14), 1615–1623. doi:10.1080/02640414.2010.521168
Chow, J. Y. (2013). Nonlinear learning underpinning pedagogy: Evidence, challenges, and implications. *Quest*, *65*(4), 469–484. doi:10.1080/00336297.2013.807746
Cordovil, R., Araújo, D., Davids, K., Gouveia, L., Barreiros, J., Fernandes, O., & Serpa, S. (2009). The influence of instructions and body-scaling as constraints on decision-making processes in team sports. *European Journal of Sport Science*, *9*(3), 169–179. doi:10.1080/17461390902763417
Davids, K. (2012). Learning design for nonlinear dynamical movement systems. *The Open Sports Sciences Journal*, *5*(1), https://benthamopen.com/ABSTRACT/TOSSJ-5-9.
Davids, K., Araújo, D., Correia, V., & Vilar, L. (2013). How small-sided and conditioned games enhance acquisition of movement and decision-making skills. *Exercise and Sport Sciences Reviews*, *41*(3), 154. doi:10.1097/JES.0b013e318292f3ec
Farrow, D., & Robertson, S. (2017). Development of a skill acquisition periodisation framework for high-performance sport. *Sports Medicine*, *47*(6), 1043–1054. doi:10.1007/s40279-016-0646-2
Fleay, B., Joyce, C., Banyard, H., & Woods, C. (2018). Manipulating field dimensions during small-sided games impacts the technical and physical profiles of Australian footballers. *Journal of Strength and Conditioning Research*, *32*(7), 2039–2044. doi:10.1519/JSC.0000000000002423
Glazier, P. S. (2017). Towards a grand unified theory of sports performance. *Human Movement Science*, *56*, 139–156. doi:10.1016/j.humov.2015.08.001
Greenwood, D., Davids, K., & Renshaw, I. (2012). How elite coaches' experiential knowledge might enhance empirical research on sport performance. *International Journal of Sports Science & Coaching*, *7*(2), 411–422. doi:10.1260/1747-9541.7.2.411
Hahsler, M., & Johnson, I. (2020). *ArulesCBA: Classification based on association rules* (R package version 1.2.0) [Computer software]. https://CRAN.R-project.org/package=arulesCBA.
Kelly, D. M., & Drust, B. (2009). The effect of pitch dimensions on heart rate responses and technical demands of small-sided soccer games in elite players. *Journal of Science and Medicine in Sport*, *12*(4), 475–479. doi:10.1016/j.jsams.2008.01.010
Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174. doi:10.2307/2529310
Liu, B., Hsu, W., & Ma, Y. (1998). Integrating classification and association rule mining. *Proceedings of the Fourth International Conference on Knowledge Discovery and Data Mining*, 80–86.
Newell, K. M. (1986). Constraints on the development of coordination. In M. Wade & H. Whiting (Eds.), *Motor development in children: Aspects of coordination and control* (pp. 341–360). Dordrecht, The Netherlands: Martinus Nijhoff.
Newell, K. M., Liu, Y.-T., & Mayer-Kress, G. (2001). Time scales in motor learning and development. *Psychological Review*, *108*(1), 57.
Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup. *European Journal of Sport Science*, *18*(10), 1309–1316. doi:10.1080/17461391.2018.1486459
Pocock, C., Bezodis, N. E., Wadey, R., & North, J. S. (2020). Understanding key constraints and practice design in Rugby union place kicking: Experiential knowledge of professional kickers and experienced coaches. *International Journal of Sports Science & Coaching*, *15*(5–6), 631–641.
R Core Team. (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/.
Renshaw, I., Chow, J. Y., Davids, K., & Hammond, J. (2010). A constraints-led perspective to understanding skill acquisition and game play: A basis for integration of motor learning theory and physical education praxis? *Physical Education and Sport Pedagogy*, *15*(2), 117–137. doi:10.1080/17408980902791586
Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. doi:10.1080/02640414.2018.1555905
Sarmento, H., Clemente, F. M., Harper, L. D., Costa, I. T., Owen, A., & Figueiredo, A. J. (2018). Small sided games in soccer – A systematic review. *International Journal of Performance Analysis in Sport*, *18*(5), 693–749. doi:10.1080/24748668.2018.1517288
Silva, P., Duarte, R., Sampaio, J., Aguiar, P., Davids, K., Araújo, D., & Garganta, J. (2014). Field dimension and skill level constrain team tactical behaviours in small-sided and conditioned games in football. *Journal of Sports Sciences*, *32*(20), 1888–1896. doi:10.1080/02640414.2014.961950
Silva, P., Esteves, P., Correia, V., Davids, K., Araújo, D., & Garganta, J. (2015). Effects of manipulations of player numbers vs. field dimensions on inter-individual coordination during small-sided games in youth football. *International Journal of Performance Analysis in Sport*, *15*(2), 641–659. doi:10.1080/24748668.2015.11868821
Timmerman, E. A., Farrow, D., & Savelsbergh, G. J. (2017). The effect of manipulating task constraints on game performance in youth field hockey. *International Journal of Sports Science & Coaching*, *12*(5), 588–594. doi:10.1177/1747954117727659
Timmerman, E. A., Savelsbergh, G. J. P., & Farrow, D. (2019). Creating appropriate training environments to improve technical, decision-making, and physical skills in field hockey. *Research Quarterly for Exercise and Sport*, *90*(2), 180–189. doi:10.1080/02701367.2019.1571678
Woods, C. T., McKeown, I., Rothwell, M., Araújo, D., Robertson, S., & Davids, K. (2020). Sport practitioners as sport ecology designers: How ecological dynamics has progressively changed perceptions of skill "acquisition" in the sporting habitat. *Frontiers in Psychology*, *11*, 654. doi:10.3389/fpsyg.2020.00654

VICTORIA UNIVERSITY

THE NEW WAY TO DO UNI

OFFICE FOR RESEARCH TRAINING, QUALITY AND INTEGRITY

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)

Title of Paper/Journal/Book: The influence of environmental and task constraint interaction on skilled behaviour in Australian Football

https://doi.org/10.1080/17461391.2021.1958011

Surname: Teune First name: Ben

Institute: Institute for Sustainable Industries and Liveabl Candidate's Contribution (%): 75

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 26/07/2021

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] 27/07/2022

Signature Date

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

1. They meet criteria for authorship in that they have participated in the conception, execution or interpretation of at least that part of the publication in their field of expertise;
2. They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;

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

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

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 storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Carl Woods	5	Assisted with theoretical positioning, feedback and revisions	[redacted]	18/07/22
Alice Sweeting	5	Assisted with methodology, feedback and revisions		19/07/22
Mathew Inness	5	Assisted with feedback and revisions		26/07/22
Sam Robertsons	10	Assisted with concept and study design, feedback and revisions		27/07/22

Updated: September 2019

The influence of environmental and task constraint interaction on skilled behaviour in Australian Football

4.1 Abstract

The design of sports practice environments can be informed through data collected and analysed according to principles of the constraints-led approach. In this study, three manipulated environmental (area per player, number of players and team outnumber) and two task (activity objective and disposal limitations) constraints were measured during professional Australian Football training activities (n = 112) to determine their relationship with skilled behaviour. Linear regression modelling of the five manipulated constraints explained 68% of the variance in disposal frequency but only 22% in skill efficiency. Activities with scoring objectives, limited to kicking or which permitted all disposals, reduced the disposal frequency per player. Activities which permitted all disposals were also weakly, negatively associated with skill efficiency. A Classification Based on Association analysis measured the interaction between manipulated constraints and their relationships with possession time and pressure. When compared to the null model, the analysis improved pressure classification accuracy by 5.9% and did not improve possession time classification accuracy. This indicates skills were often performed under varying spatial and temporal constraints during many of the training activities. This study presents multivariate analytical methods which consider constraint interaction, enhancing how practitioners can evaluate and inform training design in sport.

4.2 Introduction

Designing practice environments that support athlete learning and improve performance is an important consideration for sports practitioners (Davids, 2012). A framework commonly used to guide the design of such practice environments is the constraints-led approach (Newell, 1986). In this framework, constraints are viewed as boundaries, occurring over varying timescales, that shape emergent behaviour of individuals and groups (Newell et al., 2001). Constraints can be categorised into task, performer and environmental classes (Newell, 1986). In sport, task constraints relate to the intent of the activity, inclusive of the rules or equipment used. Performer constraints pertain to the individual, including their anthropometric attributes and physiological qualities. Environmental constraints typically include features external to the performer, and may include the weather, lighting or field dimensions (Newell, 1986).

By identifying constraints which are most influential on athlete behaviours during competition, practitioners can carefully design them into practice tasks – amplifying or dampening them to help channel or guide certain behaviours during training (Renshaw et al., 2010). These manipulations should encourage problem-solving and facilitate athlete-environment interactions (Woods, McKeown, Rothwell, et al., 2020). Evaluation of these manipulations can then determine whether the desired behavioural outcome is being functionally achieved. Athlete behaviour responses to the intentional manipulation of constraints in practice design have been examined across a variety of sports. For example, manipulations of field size can be inversely related to the frequency of some team-sport actions, such as interceptions, shots on goal or tackles (Casamichana & Castellano, 2010; Fleay et al., 2018). Decreasing the number of players in a practice task can increase the number of actions performed per player, such as (un)successful passes or dribbles (Sarmento et al., 2018; Timmerman et al., 2019), while creating a team imbalance (i.e., 6 vs 5) may increase the proportion of successful passes completed in Australian Football (AF) small side games (Bonney et al., 2020).

An ongoing methodological challenge in the modelling of athlete behaviour during training and competition is that constraints do not function in isolation, but interact dynamically and often non-linearly (Newell, 1986). For example, in youth football, playing space and the distance between players may be influenced by the interaction of field dimensions (environmental constraint), skill level (performer constraint) and playing numbers (task constraint) (Silva, Duarte, et al., 2014; Silva et al., 2015). In field hockey, both field characteristics and playing numbers influenced action frequencies – increasing or decreasing them based on the emergent time and task goals (Timmerman et al., 2019). Considering how constraints interact may provide practitioners with greater context, potentially improving their understanding on how they can design training environments to facilitate athlete learning. Therefore, measuring multiple constraints and utilising analytical methods which account for these interactions is recommended (Browne, Sweeting, et al., 2019; Robertson et al., 2019a). Practically, constraint measurement is typically limited by resources and costs, meaning no model can be fully complete. However, as the feasibility of capturing constraints in the field is increased due to technological improvements, furthering this methodology presents a worthwhile exercise. Rule induction represents one such analysis approach that is fit for the purpose of this exercise. Specifically, it focusses on identifying the most commonly occurring and influential patterns in data, an approach that closely matches the human method of heuristics (Agrawal et al., 1996). In a scenario of growing data volume, this encourages the user to focus on only those non-linear interactions which are most important in terms of modelling a phenomenon of interest.

A rule induction method for analysing constraint interaction was recently utilised to evaluate kicks during AF match play (Robertson et al., 2019a) and has been contrasted with univariate analysis (Browne, Sweeting, et al., 2019). For example, Browne et al. (2019) noted that when compared with univariate analysis, rule induction provided a more comprehensive insight into the kicking performance of Australian footballers. This was manifest in kicks under physical pressure being more accurate when coupled with task constraints of longer possession time and kicks to targets that were unmarked or unopposed. Using similar analysis, the current study aims to ascertain the strength of relationship between task and environmental constraints manipulated as part of the training design, and a) their effects on the frequency and effectiveness of skill involvements, and b) the prevalence of constraints on skill involvements.

4.3 Methodology

4.3.1 Participants

Participants were listed players (n = 43; 24.2 ± 3.5 y; 186.8 ± 7.7 cm; 84 ± 7.8 kg) from one professional AF club. All participants provided written informed consent and were injury free at the time of participation in the selected activities. Ethical approval was obtained from the University Ethics Committee.

4.3.2 Data Collection

Data collection occurred during the club's 2020 Australian Football League pre-season training period. Training activities (n = 112) with environmental and task constraint manipulations were captured, consisting of 20 different activity types and 3907 skill involvements. To obtain information on training design, five manipulated constraints were used: three environmental and two task constraints (Figure 4.1). The constraints selected were based on the literature (Bonney et al., 2020; Timmerman et al., 2019) and consultation with expert AF coaches at the club. For each drill, the total number of players and team outnumber were recorded, with the field dimensions manually recorded using a measuring wheel. Activity objective (i.e., possession or scoring) and disposal limitation (i.e., handballs, kicking or all disposals) were additionally recorded.

Figure 4.1 Manipulated environmental and task constraints (left) and constraints on skill involvements (right) with associated levels where appropriate.

To record each skill involvement, activities were filmed at 25 Hz with a two-dimensional camera (Canon XA25/Canon XA20) from either a side-on or behind-the-goals perspective. Cameras were situated in a fixed position and vision angle varied depending on location of drill at the time of performance. To quantify skill involvements and the surrounding task constraints, notational analysis software was used (Sportscode, version 12.2.10, Hudl). A customised code window was created whereby each skill involvement was recorded according to 'type' (kick or handball) and 'outcome' (effective or ineffective). The effectiveness of the skill involvement was defined in accordance with Champion Data (Melbourne, Pty Ltd), with a handball or kick <40 m deemed effective, if the intended target retained ball possession. A kick >40 m was deemed effective if kicked to a 50/50 contest or outnumber to the advantage of the attacking team. Effectiveness was represented as skill efficiency (%), defined as the number of effective skill involvements in each drill relative to the total number of skill involvements. Disposal frequency was represented as the total number of disposals relative to the duration of the activity and the number of players in the activity (disposals / min / player). To capture the task constraints on each skill involvement, the Sportscode window was used to add additional labels, defined through consultation with club coaches and adapted from the literature (Robertson et al., 2019a). As shown in Figure 4.1, time in possession was discretised into two groups; <2 s or ≥2 s and pressure was categorised as present or absent. Pressure was defined by the presence of an opposition player within 3m of the passer at moment of ball disposal (Robertson et al., 2019a). Efficiency, disposal frequency, time in possession and pressure were then exported, according to their drill, into a custom Microsoft Excel spreadsheet. Constraint manipulation data and skill involvement data were then joined according to the training activity, forming a single database.

To assess the intra-rater reliability of the skill involvement coding, three activities consisting of 145 involvements were coded on two separate occasions with at least 14 days between. The Kappa statistic was used to assess intra-rater reliability of each variable (Landis & Koch, 1977). Agreement was “almost perfect” for time in possession (0.83) and effectiveness (0.93) and “substantial” for pressure (0.79).

4.3.3 Statistical Analysis

All statistical analysis occurred in R (R Core Team, 2019). To address the first aim, two multiple linear regression models were used to determine the relationship between the manipulated environmental constraints (area per player, number of players and team outnumber) and task constraints (drill objective and disposal limitations) and their effect on a) disposal frequency and b) skill efficiency.

To determine the influence of task and environmental constraints on the time in possession and pressure of each skill involvement, a Classification Based on Association (B. Liu et al., 1998) approach was utilised. The Classification Based on Association (B. Liu et al., 1998) creates a model to predict the class of a variable based upon association rules mined in a dataset. A default rule is also generated in the model for which a class prediction is made for items which do not meet the mined rules. Each rule is presented with associated support and confidence levels.

Support (%) is a measure for how frequently a rule appeared in the database and confidence (%) measures the frequency of a class, given the associated rule.

The *ArulesCBA* package (Hahsler & Johnson, 2020) was used to run the *CBA* algorithm (B. Liu et al., 1998) to construct two models; classification of time in possession and pressure. A random sample of 70% (2734 skill involvements) of the dataset was selected for classifier training. To prepare the data for analysis, discretisation of the area per player, number of players and team outnumber variables was conducted through the *ArulesCBA* package which used the minimum description length principle to bin data. The breaks for each discretisation in the time in possession model were: area per player; 93, 249, 276, 267, 590, number of players; 15 and team outnumber; 1, 4.5. The breaks for each discretisation in the pressure model were: area per player; 131, 235, 263, 276, 451, 522, number of players; 9 and team outnumber; 4.5. Parameters for both constructed models were set with a minimum support of 0.03 and minimum confidence of 0.5. Both models were required to use rules with five items representing each of the manipulated constraints and pruning occurred with the M1 method. The models constructed from the training data were then used to predict classification of time in possession and pressure on the remaining 30% (1173 skill involvements) of the dataset. Classification accuracy of the two models were evaluated with a confusion matrix.

4.4 Results

All descriptive statistics are reported as a mean and standard deviation. Across all activities, the mean area per player was 338 ± 269 m^2, mean number of players was 12 ± 4.3 and mean team outnumber was 0.7 ± 1.2. Within the dataset, 40% of activities were limited to handballs, 12% were limited to kicks and 48% permitted all disposals. Activities with possession-based objectives comprised 15% of the dataset whilst activities with scoring-based objectives was 85%. Mean skill efficiency across all activities was 80.9 ± 9.13% and mean disposals per player per minute was 0.81 ± 0.38.

As displayed in Table 4.1, the linear regression models showed the manipulated environmental and task constraints had a stronger relationship with disposal frequency (Adjusted R^2 = 0.679) than skill efficiency (Adjusted R^2 = 0.216). The relationship between manipulated constraints and disposal frequency and skill efficiency is visualised in Figure 4.2. Activities permitting all disposals (t = -7.475), limited to kicking only (t = -5.536) or with a scoring objective (t = -4.220) had strong negative relationships with disposal frequency. Area per player (t = 1.079) and team outnumber (t = 0.646) had weak positive associations with disposal frequency (Table 4.1). Activities permitting all disposals (t = -3.502) also had a strong negative relationship with skill efficiency. Area per player (t = 1.123), the number of players (t = -0.748), team outnumber (t = 1.685) and scoring objectives (t = -1.309) each had weak associations with skill efficiency (Table 4.1).

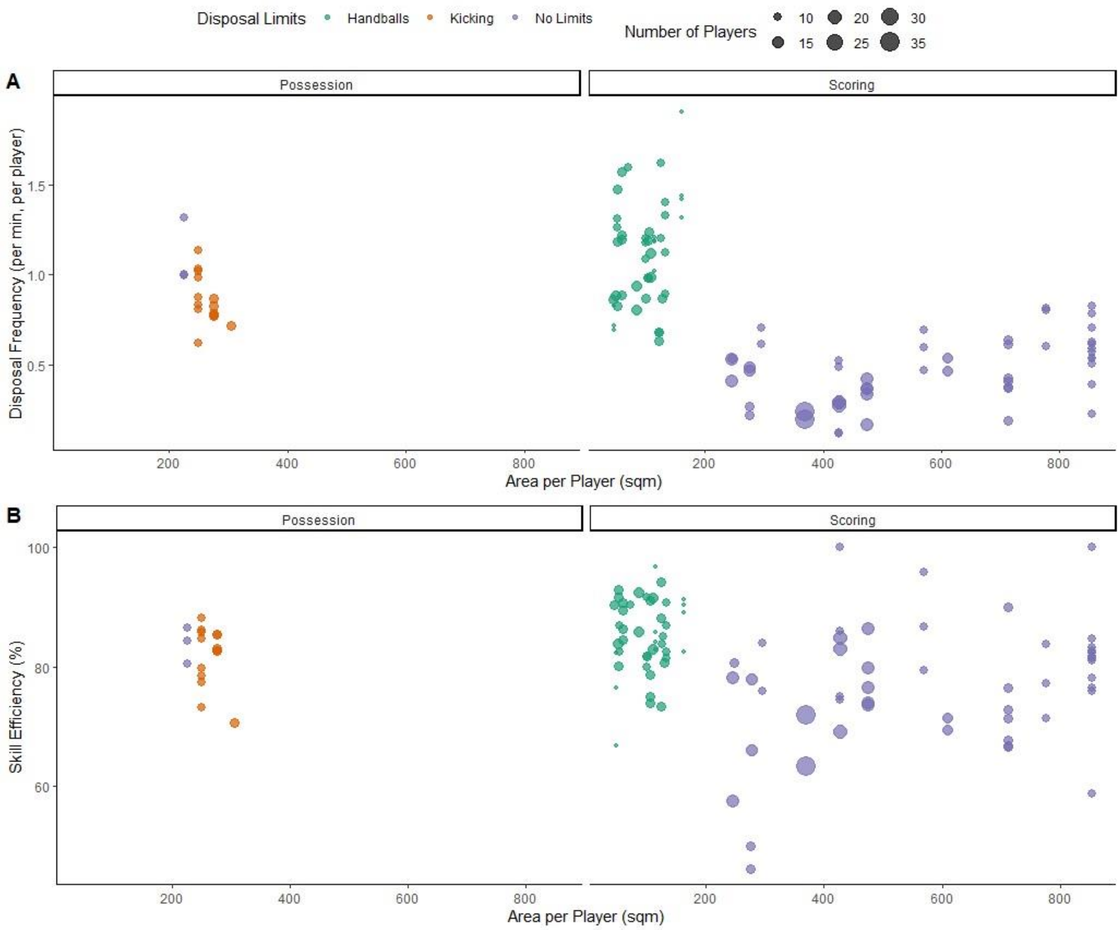


Figure 4.2 Relationship between manipulated environmental (area per player and number of players) and task (activity objective and disposal limitations) constraints and disposal frequency (A) and skill efficiency (B). Disposal frequency is reported as disposals, per min, per player and skill efficiency is reported as the number of effective involvements relative to total involvements (%). Each point represents a single training activity.

Table 4.1 Results of multiple linear regression analysis between manipulated environmental and task constraints and disposal frequency (Model 1) and skill efficiency (Model 2).

	Model 1 *Disposal Frequency*			Model 2 *Skill Efficiency*		
	B	*SE*	*t*	*B*	*SE*	*t*
(Intercept)	1.880 ***	0.145	12.954	93.596 ***	5.508	16.992
Area per Player (m^2)	0.0001	0.0001	1.079	0.007	0.006	1.123
Number of Players	-0.014 *	0.006	-2.436	-0.163	0.218	-0.748
Team outnumber	0.014	0.021	0.646	1.373	0.815	1.685
Activity Objective: Scoring[a]	-0.632 ***	0.150	-4.220	-7.435	5.682	-1.309
Disposal Limits: Kicking[b]	-0.945 ***	0.171	-5.536	-14.753 *	6.480	-2.277
Disposal Limits: No Limits[b]	-0.707 ***	0.095	-7.475	-12.582 ***	3.593	-3.502
Adjusted R^2		0.679			0.216	

*** p < 0.001, ** p < 0.01, * p < 0.05.

B = coefficient, *SE* = standard error of the coefficient, *t* = test statistic.

[a]Activity Objective: Possession used as reference category.

[b]Disposal Limits: Handballs used as reference category.

For the time in possession constraint, the proportion of each class was: <2 s = 66% and ≥2 s = 34%. For the pressure constraint, each class was: None = 58% and Pressure = 42%. The time in possession classifier resulted in seven rules, and the pressure classifier five, as displayed in Table 4.2. Excluding the default rule, which makes a prediction for items which do not meet the rules produced in the model, rules produced to classify time in possession ranged from 60% to 95% confidence. Rules to classify pressure ranged from 74% to 84% confidence. The confusion matrix revealed the time in possession and pressure classifiers had accuracies of 66% and 63.9%, respectively. Using the majority constraint class in the dataset (<2 s = 66%) as a threshold, the time in possession classifier did not improve class prediction accuracy. However, the pressure classifier slightly improved class prediction accuracy (+5.9%), compared to the majority constraint class (None = 58%).

Table 4.2 Rulesets for the time in possession and pressure Classification Based on Association models. The time in possession and pressure class is predicted based on the five associated manipulated constraints with support and confidence provided for each rule. Rules are ordered by confidence with a default rule provided for each model.

Model	Area per Player (m^2)	Number of Players	Team Outnumber	Activity Objective	Disposal Limits	Constraint Class	Support (%)	Confidence (%)
Time in Possession	248-263	0-15	1-4.5	Possession	Kicking	<2 sec	9.9	95.4
	92.9-248	0-15	1-4.5	Possession	All Disposals	<2 sec	3.5	84.4
	0-92.9	0-15	0-1	Scoring	Handballs	<2 sec	10.6	83.4
	263-276	0-15	1-4.5	Possession	Kicking	<2 sec	4.6	72.1
	92.9-248	0-15	0-1	Scoring	Handballs	<2 sec	14.9	62.5
	276-590	15-Inf	0-1	Scoring	All Disposals	>2 sec	8.8	60.3
						<2 sec	65.8	65.8
Pressure	235-263	9-Inf	0-4.5	Possession	Kicking	None	8.7	84.1
	523-Inf	9-Inf	0-4.5	Scoring	All Disposals	None	13.1	76.4
	131-235	9-Inf	0-4.5	Scoring	Handballs	Pressure	3.1	75.8
	276-451	9-Inf	0-4.5	Scoring	All Disposals	None	8.7	73.6
						Pressure	42.4	42.4

4.5 Discussion

This study demonstrated how environmental and task constraint manipulations can be evaluated to determine their influence on skilled behaviour in AF. The constraints manipulated in the current study were more influential on disposal frequency than skill efficiency, with disposal frequency more predictable than skill efficiency. Further, using an analysis approach such as Classification Based on Association highlighted the non-linearity of constraint interaction. The analysis only slightly improved, upon the majority class threshold, the classification accuracy of pressure and did not improve possession time classification accuracy. This demonstrated the tendency for activities to comprise skill involvements in different classes of constraints, indicating variable participant behaviour. This means participants were exposed to skill involvements in a range of performance contexts. Measurement of athlete skill variability can assist practitioners to evaluate if training aims are being achieved.

Linear regression modelling was used to determine the relationship between manipulated task and environmental constraints and disposal frequency, explaining 67.9% of the variance in disposal frequency. This result highlights the capability of models to predict, with some certainty, the disposal frequency of players in activities. This information could be beneficial for practitioners when estimating skill volumes, which has application for planning training designs (Farrow & Robertson, 2017) and prescribing training loads for rehabilitating athletes. A caveat to this application is that behaviour will still vary between players, manifest through things like playing position, ability, age (Almeida et al., 2016), height (Cordovil et al., 2009), and/or previous experience (Pocock et al., 2018), which will require consideration. This caveat serves as an important avenue for future work to extend on the current findings. Area per player did not influence disposal frequency, which is in agreement with similar work in AF (Fleay et al., 2018) and other team-sports (Casamichana & Castellano, 2010; Kelly & Drust, 2009). However, area per player can influence other action frequencies not measured in the current study, such as tackles and interceptions (Casamichana & Castellano, 2010; Fleay et al., 2018; Kelly & Drust, 2009).

Activities with a scoring objective, limited to kicking only or which permitted all disposals, were most associated with decreasing the mean disposal frequency per player. Accordingly, permitting kicks to occur within a drill, in addition or exclusion to handballs, decreased disposal frequency. Execution of the kicking action takes longer than the handball, however this result may also be partially explained by the rules of AF. In AF, catching a kicked pass over 15 m (a "mark") results in a stoppage of play which acts as a task constraint on behaviour. When kicking is permitted, players may be exploiting this task constraint to afford themselves additional time for decision making. This behaviour slows the play of the drill, reducing the volume of disposals accrued. AF practitioners may want to consider this when determining the length of time for activities to provide players enough time to accrue desired action opportunities. More generally, it is advised that sport practitioners consider how task constraints may increase or decrease the frequency of action opportunities provided to their athletes.

Manipulating the number of players in the drill was also shown to influence disposal frequency, albeit to a lesser extent than disposal limitations or drill objective. This result is similar to research in field hockey (Timmerman et al., 2019), but dissimilar to other work in AF (Bonney et al., 2020). Results from the present study may be due to the larger manipulations of playing number. Importantly, reducing playing number increases opportunities for players to explore possible movement solutions (Davids et al., 2013), while offering a simple and effective constraint manipulation available for coaches.

Modelling of skill efficiency was not as accurate as for disposal frequency, explaining only 26% of the variation. Similar results were observed when modelling rugby place kick performance during match play, explaining 28% variance (Pocock et al., 2018). Additional, or alternative, constraints may be required to predict skill efficiency more accurately. Skill efficiency, or relative frequency of skill errors, may be indicative of how challenging a training drill is for players (Farrow & Robertson, 2017). This is an important consideration for training design as an appropriately challenging environment may promote exploration for new movement solutions (Davids et al., 2013; Renshaw et al., 2010). It should be noted that the 2019 competition average disposal efficiency was 71.5% (obtained from https://www.afl.com.au/stats) compared to 80.9% in the present study. This may mean that the constraints manipulated during training presented a less challenging environment to players.

In the present study, activities which permitted all disposals or were limited to kicking only were most associated with reducing skill efficiency. This may indicate that kicking was a more difficult skill to execute than handballing. Similarly, in soccer, the success of passes and interceptions during small side games has been influenced by manipulating the task constraint of scoring mode (Almeida et al., 2016). Manipulating the team outnumber or area per player did not influence skill efficiency in the present study, which conflicts with other small sided game research in AF (Bonney et al., 2020) and field hockey (Timmerman et al., 2017). These results may be explained by the higher skill level of the current study's participants who can express greater skill proficiency adapted across a variety of conditions.

A multivariate analysis is more appropriate for understanding skilled behaviour (Browne, Sweeting, et al., 2019; Robertson et al., 2019a). In the present study, a Classification Based on Association approach determined the interactions between manipulated task and environmental constraints and their influence on the possession time and pressure on skill involvements. The variable rulesets, and associated confidence levels produced in the two models demonstrate the non-linearity of environmental and task constraint interaction during training. The complexity of constraint interaction is similarly exemplified during match play in other AF work (Browne et al., 2020; Browne, Sweeting, et al., 2019). It is suggested that coaches seeking to apply principles of the constraints-led approach should measure and analyse constraint manipulations in a multivariate manner to appropriately contextualise player behaviour during training. Capturing detail in this way can provide further insight into *how* and *why* certain behaviours emerge (Glazier, 2017).

Each rule presented in the models demonstrate the adaptive behaviour of players within training activities. Accordingly, this highlights how practitioners can facilitate skill development through the design of training environments (Woods, McKeown, Rothwell, et al., 2020). Practically, Classification Based on Association can be utilised to assist coaches in achieving this by informing training design. For example, a coach may seek to develop player skill by increasing the temporal demands on players when passing. The rules presented in the possession time classifier (Table 4.2) can inform the coach of the relevant constraint manipulations which achieve this. For example, the top row of Table 4.2 shows the set of constraint manipulations which maximise the frequency of skill involvements with <2 s possession time (95%). Thus, using Classification Based on Association, a practitioner could evaluate the behaviour of players within training activities and use this to inform future drill prescription.

Neither classification model was able to substantially improve, upon the majority class threshold, the accuracy of predicting time in possession or pressure. Accordingly, this indicates that many of the activities in the dataset did not constrain participants to a high frequency of skill involvements in a single class of time in possession or pressure. This demonstrates the inherent variability of AF small side games which can promote movement performance in a range of contexts (Davids et al., 2013). These results may be an example of training which encourages athletes to explore different movement solutions to achieve tasks (Chow, 2013). Thus, evaluating the accuracy of predictive models may help practitioners measure the functional variability in training, where low prediction capability is not always viewed as a negative outcome.

Importantly, it should be noted that the proportion of constraint classes and manipulations across the dataset are representative of the participant coaching and playing styles. Team strategy and coaching philosophies will likely influence the focus of training sessions, guiding the design and selection of training activities. Results of the current study are population specific and practitioners are encouraged to utilise a similar methodology, as presented here, to inform their own training. Through a multivariate analysis, such as Classification Based on Association, practitioners can further contextualise their athlete's behaviour, evaluating and informing their own constraint manipulations in the field.

Given the applied nature of this study, there were some limitations which should be stated. Skill involvement data were collected in the field where constraint manipulation was not systematic but designed by coaches as desired for any given session. The representation of some constraint manipulations and constraint classes in the dataset are unequal, potentially influencing some results. Future work should be directed to collecting additional constraints to include in analyses to aide in constructing more sophisticated models. Environmental constraints such as weather or performer constraints such as age or playing experience may play an important role in influencing skilled behaviour during training. The inclusion of coach experiential knowledge is recommended to identify these key constraints (Greenwood et al., 2012; Pocock et al., 2020).

4.6 Conclusion

This study examined the relationship between environmental and task constraint manipulations with skilled behaviour in elite AF. Constraint manipulations explained more variance in disposal frequency than skill efficiency. Designing activities that have a scoring objective and permitted kicking tended to reduce the disposal frequency of players. Designing activities which permitted any disposal method were most associated with a decrease in skill efficiency, creating a more challenging environment for players. A Classification Based on Association approach highlighted the variability of training activities and demonstrated how multivariate analysis can be used to determine constraint interaction, including influencing possession time and pressure on skill involvements. To enhance athlete skill development, practitioners are encouraged to measure interacting constraint manipulations, using similar multivariate analysis, to evaluate and inform their own training design.

CHAPTER FIVE – STUDY III

Chapter Overview

Chapter Five is the third of five studies contained in this thesis. This chapter builds upon the Chapter Four by including the additional class of individual constraints in the analysis of training activities and by applying alternative analytical techniques. Specifically, this study explores how the interaction between individual, environmental and task constraints may be measured to evaluate skilled behaviour and inform training design in AF.

The content of this chapter is an accepted manuscript of an article published by Taylor & Francis in Journal of Sports Sciences on 16th September 2022, available at: https://www.tandfonline.com/doi/full/10.1080/02640414.2022.2124013

JOURNAL OF SPORTS SCIENCES
https://doi.org/10.1080/02640414.2022.2124013

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training

Ben Teune[a,b], Carl Woods[a], Alice Sweeting[a], Mathew Inness[a,b] and Sam Robertson[a]

[a]Institute for Health and Sport (Ihes), Victoria University, Melbourne, Australia; [b]Football Department, Western Bulldogs, Melbourne, Australia

ABSTRACT

An important consideration for sport practitioners is the design of training environments that facilitate skill learning. This study presented a method to determine individual (age, games played, height, mass, and position), environmental (activity type) and task (pressure and possession time) constraint interaction to evaluate player training behaviour. Skill actions (n = 7301) were recorded during training activities (n = 209) at a single professional Australian Football club and four measures of player behaviour were determined: disposal frequency, kick percentage, pressure, and possession time. K-means clustering assigned training activities into four groups, with regression trees used to determine the interaction between constraints and their influence on disposal frequency and type. For most regression trees, only the environmental constraint was included. This showed all players adapted similarly to the constraints of each training activity. In one exception, a critical value of 60 games experience was identified as an individual constraint which interacted with activity type one to influence disposal frequency. Practically, this individual constraint value could be used to guide training design by grouping players of similar experience together. This study is presented as a practical tool for sport practitioners, which considers constraint interaction, to evaluate player behaviour and inform training design.

ARTICLE HISTORY
Accepted 6 September 2022

KEYWORDS
Small side games; team sport; coaching; skill acquisition; performance analysis; training design

Introduction

An important consideration for sport practitioners relates to the design of training environments that can facilitate skill learning (Davids, 2012). Training, then, is an important component of the coaching process, especially in high performance sport (Hodges & Franks, 2002; Orth et al., 2019). Moreover, it is the design of game-like training tasks that are particularly important to support the development of an athlete's skill (Chow, 2013; Davids et al., 2008). What makes training design challenging, is that skill is an emergent phenomena that results from the various interactions of the person (i.e., the athlete), the environment they perform in, and the task they are undertaking (Araújo et al., 2006; Newell, 1986). In other words, it is a confluence of interacting constraints that shapes the emergence of skill, and the goal of the coach in training design, then, is to nudge or guide athletes towards useful movement and performance solutions (Woods et al., 2020).

The constraints-led approach (CLA) is a framework that can be used to help practitioners with the design of practice tasks (Davids et al., 2008; Renshaw et al., 2010). In this framework, constraints are understood as boundaries, which exist along multiple time-scales, that shape the emergent actions of individuals (Newell, 1986; Newell et al., 2001). Broadly, constraints are classified into one of three classes: task, environmental and individual (Newell, 1986). In sport, task constraints typically relate to the intent of an activity; what needs to be achieved and within what time. Environmental constraints include features external to the performer, such as ambient weather conditions, ground surface properties, and field size. Individual constraints pertain to characteristics of a performer, like anthropometric and physiological qualities, or emotional states and arousal levels.

In harnessing tenets of the CLA, practitioners can guide athlete behaviour through the careful manipulation of constraints in practice tasks (Renshaw & Chow, 2019; Renshaw et al., 2010). For example, reducing field size can increase the frequency of interceptions in soccer (Casamichana & Castellano, 2010), or manipulating a team outnumber can increase the frequency of passes to uncovered players in Australian Football[1] (Bonney et al., 2020). The manipulation of key constraints encourages problem-solving and facilitates an athlete's exploration for movement solutions (Woods et al., 2020). Thus, to assist with athlete learning, the evaluation of constraint manipulations, and how they have shaped emergent behaviour, can be of use for sports practitioners (Teune, Woods et al., 2021).

A challenge for practitioners in evaluating athlete behaviour is that constraints do not function in isolation but interact, often non-linearly (Newell, 1985). Accordingly, constraint interaction is important to consider, to protect against the influence of a constraint being over or under valued when contextualised within larger constraint sets. This increases the complexity of implementing constraint manipulations during practice and understanding their combined influence on behaviour. In field

CONTACT Ben Teune benteune@outlook.com Institute for Health and Sport, Victoria University, Melbourne, Australia

[1]Australian Football is an invasion team sport consisting of 22 (18 on field and 4 substitutes) players per team during match play where teams compete to score points by kicking goals (6 points) or behinds (1 point). In Australian Football, players are permitted to pass the ball via kicking or handballing (punching the ball with a closed fist). Furthermore, players may be allocated specific roles within a team however, roles are dynamic and not restricted by any rules (Australian Football League, 2021).

hockey, for example, the number of players (i.e., an environmental constraint) and the intent of the task, have been shown to interact, influencing the frequency of certain actions (Timmerman et al., 2019). Moreover, studies in Australian Football have examined the multivariate interaction between task and environmental constraints to evaluate match play kicking performance (Browne et al., 2019; Robertson et al., 2019), goal kicking performance (Browne et al., 2022) and skilled behaviour during training activities (Teune, Woods et al., 2021). Together, this work demonstrates how considering the interaction of multiple constraints may garner more precise insights to support practice design. However, investigations of constraint interactions have mainly been limited to environmental and task constraint classes. To build upon this work, studies which include individual constraint interactions with environmental and task constraints are largely yet to be explored. One exception in Rugby Union modelled place kicking effectiveness using logistic regression including interaction between game time (environmental constraints), score margin (environmental constraint), previous kick success (individual constraint), distance (task constraint) and angle (task constraint) to goal (Pocock et al., 2018). In this study, distance and angle to goal were found as significant variables included in a model that accurately classified 76% of kick outcomes. With this approach, threshold values which influenced kick success for distance and angle to goal were identified, information that could guide place kicking practice design.

Multivariate analytical techniques, which can consider non-linear constraint interaction, are important to appropriately contextualise player behaviour (Browne et al., 2021). Some analytical techniques, such as rule induction or decision trees, have such capabilities and have been applied to constraint analysis in Australian Football competition (Browne et al., 2019, 2022; Robertson et al., 2019) and practice (Browne et al., 2020; Teune, Woods et al., 2021). Further, unsupervised machine learning techniques such as *k*-means clustering algorithms have been applied to Australian Football to group training activities according to similarities in player performance (Corbett et al., 2018). Specifically, *k*-means clustering has been useful to identify associations between training activity design and player performance (Corbett et al., 2018). These techniques provide interpretable outputs that make them applicable for end users in sport, such as skill acquisition specialists or coaches. An adaptation of such techniques may be beneficial as a practical tool for such practitioners to evaluate team sport training while considering constraint interaction between all three classes. Therefore, the primary aim of this study was to present a method to measure the relationship between interacting task, environmental and individual constraints on skill involvement frequency and kick percentage during Australian Football training. A secondary aim was to highlight the value of determining constraint interaction in applied sport training environments.

Methods

Participants

Participants were listed Australian Football League players (n = 54, height = 187 cm ± 7.83, mass = 84.7 kg ± 7.73, age = 24.4 years ± 3.42) at a single club during the 2021–2022 seasons. All participants provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the University Ethics Committee (application number: HRE20-138).

Data collection

Data were collected on 209 training activities, consisting of 34 different activity designs. All activities were characterised as a small-sided game, where two teams competed against each other within a specified field of play. Each activity type varied in the task goals, rules, field size or number of players. Skill involvement data were collected via filming with a 25 Hz two-dimensional camera (Canon XA25/Canon XA20) from a side-on or behind-the-goals perspective. Skill involvements during each activity were coded via notational analysis software (Sportscode, version 12.2.10, Hudl) using a customised code window whereby each skill involvement (or "disposal") was labelled according to the type (kick or handball) and the player's name who performed the skill (n = 7301). Each disposal was further labelled with two task constraints: pressure (present or absent) and possession time (<2 s or >2 s), which has been the approach used in other Australian Football work (Browne et al., 2020). Pressure was defined as a disposal performed within 3 m of an opponent, while possession time was defined as the time between receiving and disposing the ball. Inter-rater reliability of the notational coding was assessed using a hold-out sample of 168 disposals, not included in the main analysis, resulting in a Kappa statistic (Landis & Koch, 1977) of "almost perfect" (>0.8) for all variables. Intra-rater reliability was conducted after a 14-day washout period resulting in Kappa statistics ranging from "substantial" (0.67–0.8) to "almost perfect" (>0.8) across three coders.

Individual constraints for each player were recorded at the beginning of each season, which were height (cm), weight (kg), number of games played (#) and playing position (defender, midfielder, forward or key position). Key position players typically consist of tall forwards and tall defenders (McIntosh et al., 2021). Age (years) was also determined as the time period between the player's date of birth and the date of training activity occurrence. Playing positions were assigned in consultation with the club's coaching staff who were familiar with individual player roles. Distributions of each individual constraint are shown in Figure 1. Skill involvement data was labelled with individual constraints according to the player's name associated with each disposal. For every training activity, each player's skilled performance was then summarised according to four measures: disposal frequency, kick percentage, pressure, and possession time. These measures were chosen through consultation with club's coaching staff and Australian Football literature (Teune, Woods et al., 2021). Disposal frequency was calculated as the total disposals divided by the activity duration in minutes, while kick percentage was represented as the percentage of kicked disposals. Pressure was represented as the percentage of pressured disposals, and possession time was represented as the percentage of disposals <2 s. These calculations resulted in 2499 individual training activity performances.

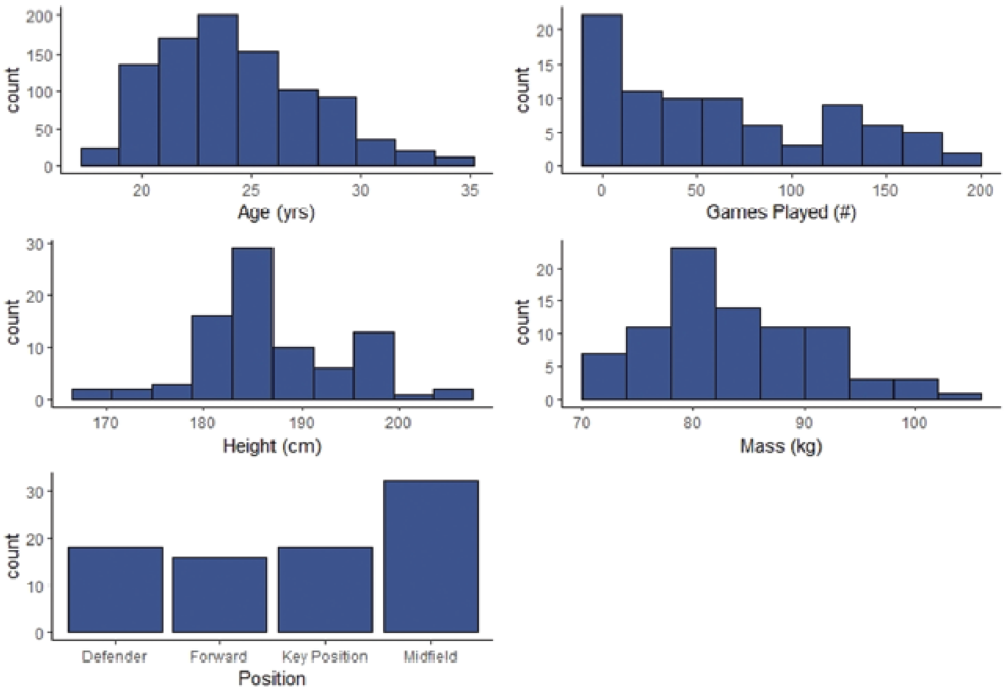


Figure 1. Distribution of each individual constraint included in analysis.

Statistical analysis

To determine the influence of constraint classes and their interactions on player skilled behaviour, four analyses were conducted. This approach was taken to demonstrate the influence of constraint classes when considered both in isolation and in combination.

In the first analysis, regression trees were used to estimate the interaction between constraints (Morgan et al., 2013). To determine the influence of individual constraints alone on player performance, two regression trees were grown, estimating disposal frequency and kick proportion, respectively. To determine the interaction between individual and task constraints, two further regression trees were grown to estimate pressure and possession time. All statistical analysis occurred in the R programming environment (R Core Team, 2019), with regression trees grown using the *rpart* package (Therneau & Atkinson, 2022). The five individual constraints were included as predictors in each of the models, and parameters were specified with a minimum split of 20 observations and a complexity parameter of 0.01.

In the second analysis, *k*-means clustering was used to identify the training activities which result in similar player outputs and were grouped accordingly to determine the influence of environmental constraints on skilled behaviour (Corbett et al., 2018). A scree plot was first generated to determine the appropriate number of clusters to use in analysis. 10 maximum iterations were permitted, with each training activity then assigned to one of the cluster memberships according to the results of the *k*-means clustering.

In the third analysis, to determine the interaction between environmental and individual constraint classes on skilled behaviour, regression trees were grown to estimate disposal frequency and kick percentage. Each of the five individual constraints and the environmental constraint of activity type were included in the two models using the same parameters as previous models.

In the fourth analysis, to determine the interaction between environmental, individual and task constraint classes, two regression trees were grown to estimate pressure and possession time. The five individual constraints and the environmental constraint of activity type were included as predictors in the model. The same model parameters were used as previous models.

Results

Across 2499 training activities, the mean and standard deviation was 0.59 ± 0.46 disposals per minute, 60.2% ± 40% kicks, 40.7% ± 39.5% pressured disposals, and 51.2% ± 40% disposals <2 s. For the two regression tree models which included only individual constraints, the first estimated disposal frequency with a mean squared error of 0.22 disposals/min. The second model estimating kick percentage had a root mean squared error of 44.02%. For the two regression trees which estimated task constraints using only individual constraints as predictors, the model estimating pressure had a root mean squared error of 39.49%. The model estimating possession time had a root mean squared error of 39.98%.

Table 1. Cluster centres (averages) of each training performance metric for drill activity memberships.

Cluster membership	Disposal Frequency (p/min)	% Kicked Disposals	% Pressured Disposals	% Disposals <2 s
1	1.11	0	61.6	66.0
2	0.69	82.0	21.3	79.4
3	0.39	78.5	28.3	33.8
4	0.45	69.5	76.2	53.0

Visual analysis of the scree plot resulted in four clusters being selected. The four cluster centres resulting from the subsequent *k*-means clustering analysis is shown in Table 1. The distributions of the player performance metrics (disposal frequency, kick proportion, pressure, and possession time) within each activity membership are shown in Figure 2. Cluster one was distinguished as handball only activities, with high levels of disposal frequency, pressure and lower possession times. Cluster two had the highest proportion of kicked disposals and disposals <2 s and the lowest level of pressure. Cluster three had the lowest disposal frequency, a high proportion of kicks with low pressure and time constraints. While cluster four was similar to cluster one in terms of pressure and possession time, it involved predominantly kicked disposals with a lower disposal frequency.

The regression trees that included environmental and individual constraints, estimating disposal frequency and kick percentage, are shown in Figures 3 and 4, respectively. The results of the tree estimating disposal frequency had a mean squared error of 0.129 disposals/min and an R squared value 0.40. Games played was the only individual constraint included in the model which was shown to positively influence disposal frequency for activities in membership one. The regression tree estimating kick percentage had a root mean squared error of 29.83% and an R squared value of 0.54. No individual constraints were included in this model.

The regression trees that included environmental and individual constraints, used to estimate task constraints, pressure and possession time, are shown in Figures 5 and 6, respectively. The results of the model estimating pressure had a root mean squared error of 34.69% and an R squared value of 0.22. The model estimating possession time had a root mean squared error of 35.62% and an R squared value of 0.21. Neither of these models included any individual constraints to partition the data.

Discussion

This study demonstrated a method to evaluate player performance in a team sport training environment by considering the interaction of individual, environmental and task constraints. Results showed that the environmental constraint of activity type was the most influential on player performance, indicating that players adapted their performance to suit the training activity design. The individual constraints collected in this study had limited influence on player performance, suggesting that coaches achieved activity designs that constrained player behaviour in a similar way, regardless of individual characteristics. In one exception however, games played showed an

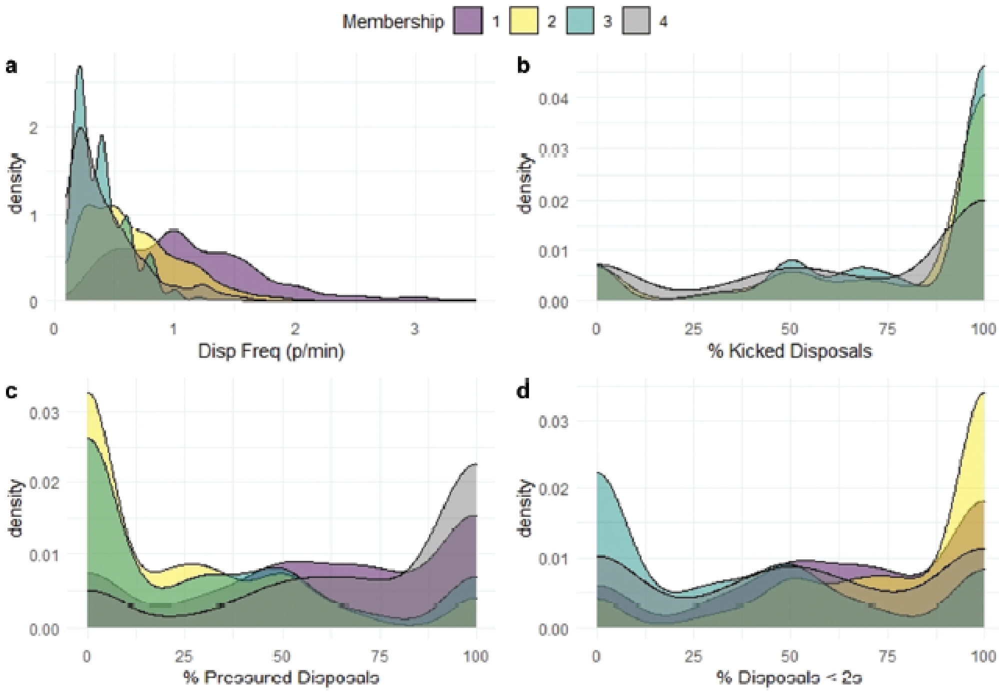


Figure 2. Distribution of training performance metrics; disposal frequency **(a)**, kick percentage **(b)**, pressure **(c)** and possession time **(d)** within each activity membership. Note, in panel **b**, data for cluster membership one has not been displayed given that no kicked disposals were recorded in this membership.

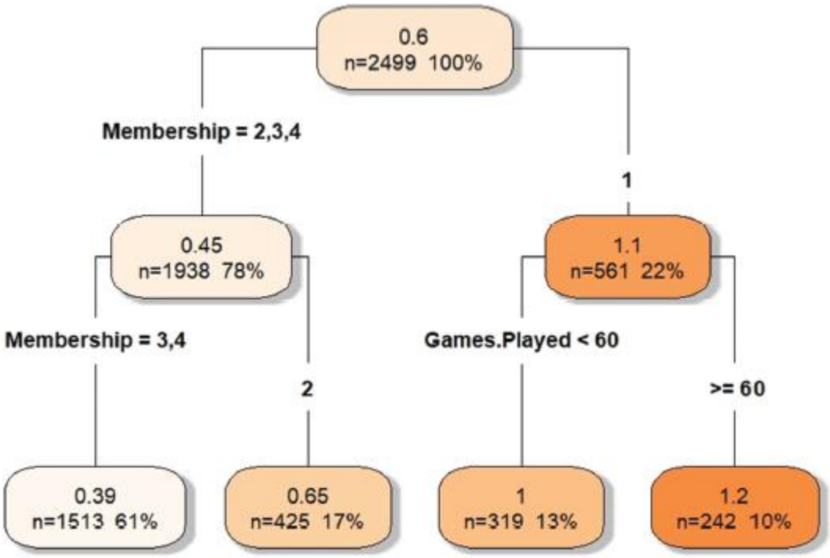


Figure 3. Regression tree modelling disposal frequency (disposals/min). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (disposals/min). The bottom values in each node represent the frequency and percentage of cases within each node.

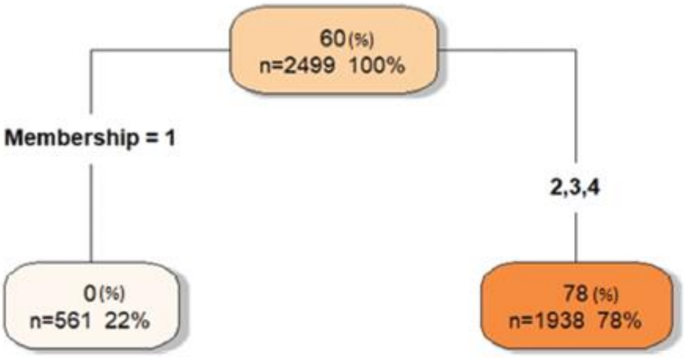


Figure 4. Regression tree modelling disposal type (% of kicked disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of kicked disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

interaction with activity type one, suggesting that experienced players were able to perform more disposals than less experienced teammates. Task and environmental constraint interaction was also noted, indicating the environmental constraint of activity type influenced the levels of the task constraints, pressure and possession time, however, the individual constraints collected in this study did not influence this.

Individual constraints, when considered alone, did not influence disposal frequency or kick percentage, nor did they influence the task constraints of pressure or possession time. This contradicts other work where individual constraints have been influential on skilled performance (Almeida et al., 2016; Cordovil et al., 2009; Pocock et al., 2018, 2021). This result may be explained by the wide range of varying activity types included in the current study, leading to variability in performance. Individual constraints are perceived by coaches as an important feature to consider in practice design (Pocock et al., 2020). However, these results indicate that there were no general trends in player performance which were applicable across all activity types. Further context to these constraints is required, thereby helping coaches evaluate player performance more effectively. This result may also mean that different or more sensitive individual constraints need to be considered in future research, inclusive of physiological qualities, such as heart rate, or psychological attributes, such as confidence level (Pocock et al., 2021).

The *k*-means clustering was beneficial to determine associations between the practitioner's activity designs and player performance, whereby activities resulting in similar player performances could be grouped. For example, the activities

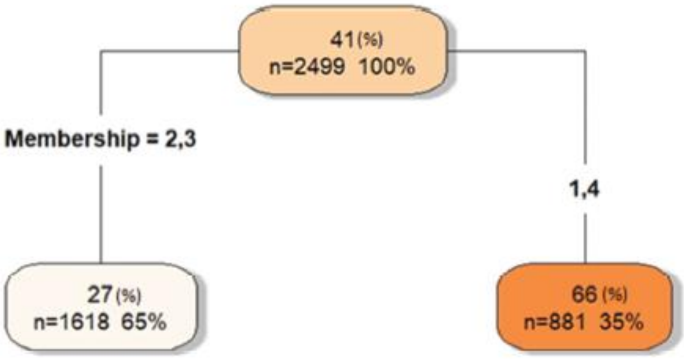


Figure 5. Regression tree modelling pressure (% of pressured disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of pressured disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

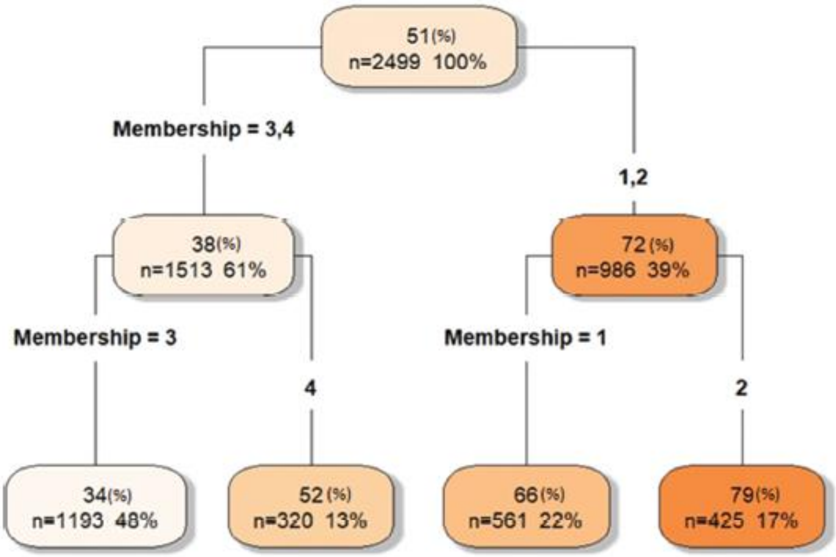


Figure 6. Regression tree modelling possession time (% of disposals <2s). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of disposals <2s). The bottom values in each node represent the frequency and percentage of cases within each node.

included in cluster one were limited to handballs only – representing tasks with a rule constraint that did not permit kicking. Contrastingly, cluster two activities were designed with constraints which encouraged a high proportion of quick kicks with low levels of pressure. This suggests, within this group of activities, that players were able to identify passing options quickly and dispose of the ball before defensive pressure could be applied. *K*-means clustering could be helpful for activity prescription, allowing coaches to select a range of activities from particular groups which meet certain training targets, such as a focus on kicking or performing disposals under pressure. Accordingly, relevant support staff, such as data analysts or skill acquisition specialists, may use such analysis to help guide the design of practice tasks through careful manipulation of constraints (Woods et al., 2020). Additionally, the clustering approach used here is flexible, meaning it can be applied to any team and across any parameters deemed important by practitioners.

Including the environmental constraint of activity type with individual constraints in the regression trees improved the model's accuracy. This result was expected, as activity type was previously grouped according to the player performance metrics. However, the individual constraints included in the models had limited capacity in explaining further variance within each activity type. This result highlights the capability of the coaches to design activities that constrain player performance similarly. Thus, the minimal influence of individual constraints is a beneficial insight for practitioners, identifying the consistent influence of their activity design across all players, regardless of individual characteristics. In one exception, an interaction between activity type one and games played influenced disposal frequency. According to the cluster centres, activity type one was characterised as a fast game with high disposal frequency using only handballs, high levels of pressure, and high levels of temporal constraints. Accordingly, within this group of activities, experience was important in shaping how often a player performed a disposal (Baker et al., 2003). This may be due to the higher skill of experienced players to perform under increased temporal and spatial constraints, positioning themselves more optimally to receive and dispose the ball. Alternatively, experienced players may be more frequently sought out by teammates as passing options.

Importantly, within activity type one, the regression tree model identified a critical value for experience of 60 games, which may be leveraged by coaches to inform individual differences in performance during this activity type. Though, it may be beneficial for coaches to utilise support from a broader staff team, including a skill acquisition specialist, to best glean such information. Indeed, the benefits of skill acquisition support has been highlighted in (para-) Olympic sports (Pinder & Renshaw, 2019; Williams & Ford, 2009). Thus, a skill acquisition specialist (perhaps working closely with performance analysts) could undertake an analysis such as that described here, to then be reported back to coaching staff as additional information which may guide how constraints can be manipulated during practice tasks. For example, in the present study, players could be divided into "more experienced" (> 60 games) and "less experienced" (< 60 games) groups. Coaches may utilise this grouping to achieve their training goals, purposefully accelerating the skill development of less experienced players by placing them against more experienced ones. Alternatively, less experienced players may train against other less experienced players, potentially increasing their disposal frequency and providing them with more learning opportunities. Less experienced players could also be provided additional training activities after the session, or the activity could be run for longer to allow these players to accrue more disposals. Regardless, this result exemplifies how the analysis can be practically implemented by skill acquisition specialists and performance analysts to assist a coach's ability to structure and plan training sessions that consider individual differences (Chow, 2013).

The environmental constraint of activity type interacted with the two task constraints of pressure and possession time however, the regression trees were only able to explain 22% and 21% of the variance in these constraints, respectively. This indicated that these constraints were highly variable within activity types and may be a result of constraint manipulations implemented by coaches which were not collected in this study. For example, field dimension or the number of players may have been manipulated from session to session, according to changes in player availability or to directly influence player performance. Indeed, field dimension and the number of players has been shown to influence player performance in Australian Football (Bonney et al., 2020; Fleay et al., 2018; Teune, Spencer et al., 2021; Teune, Woods et al., 2021). In the present study, only the environmental constraint of activity type was shown to influence the task constraints, with none of the individual constraints included in the resulting models. Accordingly, alternate or improved measures of individual constraints may need to be collected to determine their influence on player performance. For example, players were allocated into one of four positions; forward, midfield, defender or key position. However, unlike some sports, such as netball, the nature of positions in Australian Football is dynamic. More detailed position groupings may influence the models such as including small general forwards and defenders, or rucks, as used in other Australian Football work (McIntosh et al., 2018).

Given the applied nature of the current study, there are limitations that require acknowledgement. First, specific constraints such as field dimensions, number of players or task rules were not collected. This could have been manipulated by coaches between sessions and may therefore have influenced behaviour. These environmental and task constraints have been modelled in previous Australian Football work (Teune, Woods et al., 2021), however, future studies may look to include individual constraints within such models to provide deeper insight into player behaviour. Additionally, environmental constraints, like fluctuations in wind, rain, ambient temperature or time in session of the practice task were not collected, which may have influenced player performance. Future work may also measure a broader range of player behaviour metrics within training activities, including defensive skill involvements, such as tackles or intercepts, skill involvement effectiveness, or team behaviour metrics such as team separateness or surface area. Finally, given the broad time range in which data collection occurred, it is possible that player performance changed according to tactical directions of coaching staff. Thus, future work may benefit from measuring training performance adaptations over longitudinal timelines to inform training design (Farrow & Robertson, 2017).

Conclusion

This study developed a method to measure interaction between individual, environmental and task constraints during Australian Football training. The environmental constraint of activity type was the most influential on individual training performance, highlighting the achievement of coaches to design training which constrains all players similarly. The individual constraint of player experience interacted with one activity type. It was shown how the analysis can be used to identify critical constraint values, such as 60 games played, which can inform training design by allocating players into specific groupings. This study is presented as a practical tool for sport practitioners and coaches to evaluate the performance of their players during training and inform the design and structure of training activities.

List of abbreviation

CLA Constraints Led Approach

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ORCID

Ben Teune http://orcid.org/0000-0003-4437-535X

References

Almeida, C. H., Duarte, R., Volossovitch, A., & Ferreira, A. P. (2016). Scoring mode and age-related effects on youth soccer teams' defensive performance during small-sided games. *Journal of Sports Sciences*, *34*(14), 1355–1362. https://doi.org/10.1080/02640414.2016.1150602

Araújo, D., Davids, K., & Hristovski, R. (2006). The ecological dynamics of decision making in sport. *Psychology of Sport and Exercise*, *7*(6), 653–676. https://doi.org/10.1016/j.psychsport.2006.07.002

Australian Football League. (2021). *2021 Laws of the Game*. https://resources.afl.com.au/afl/document/2021/05/17/8ee25f9e-5aff-4813-9c5d-1addfa655470/2021-Laws-of-the-Game-.pdf?_ga=2.173672032.252968313.1648181475-820647460.1647339803

Baker, J., Cote, J., & Abernethy, B. (2003). Sport-specific practice and the development of expert decision-making in team ball sports. *Journal of Applied Sport Psychology*, *15*(1), 12–25. https://doi.org/10.1080/10413200305400

Bonney, N., Ball, K., Berry, J., & Larkin, P. (2020). Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. *Journal of Sports Sciences*, *30*(21), 2430–2436. https://doi.org/10.1080/02640414.2020.1787697

Browne, P., 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*, *66*, 621–630. https://doi.org/10.1016/j.humov.2019.06.013

Browne, P., Sweeting, A. J., & Robertson, S. (2022). Modelling the influence of task constraints on goal kicking performance in Australian rules football. *Sports Medicine - Open*, *8*(1), 13. https://doi.org/10.1186/s40798-021-00393-9

Browne, P., Sweeting, A. J., Woods, C. T., & Robertson, S. (2021). Methodological considerations for furthering the understanding of constraints in applied sports. *Sports Medicine - Open*, *7*(1), 22. https://doi.org/10.1186/s40798-021-00313-x

Browne, P., Woods, C. T., Sweeting, A. J., Robertson, S., & Rogan, S. (2020). Applications of a working framework for the measurement of representative learning design in Australian football. *PLOS ONE*, *15*(11), e0242336. https://doi.org/10.1371/journal.pone.0242336

Casamichana, D., & Castellano, J. (2010). Time–motion, heart rate, perceptual and motor behaviour demands in small-sides soccer games: Effects of pitch size. *Journal of Sports Sciences*, *28*(14), 1615–1623. https://doi.org/10.1080/02640414.2010.521168

Chow, J. Y. (2013). Nonlinear learning underpinning pedagogy: evidence, challenges, and implications. *Quest*, *65*(4), 469–484. https://doi.org/10.1080/00336297.2013.807746

Corbett, D. M., Bartlett, J. D., O'connor, F., Back, N., Torres-Ronda, L., & Robertson, S. (2018). Development of physical and skill training drill prescription systems for elite Australian Rules football. *Science and Medicine in Football*, *2*(1), 51–57. https://doi.org/10.1080/24733938.2017.1381344

Cordovil, R., Araújo, D., Davids, K., Gouveia, L., Barreiros, J., Fernandes, O., & Serpa, S. (2009). The influence of instructions and body-scaling as constraints on decision-making processes in team sports. *European Journal of Sport Science*, *9*(3), 169–179. https://doi.org/10.1080/17461390902763417

Davids, K. (2012). Learning design for nonlinear dynamical movement systems. *The Open Sports Sciences Journal*, *5*(1), 9–16. https://doi.org/10.2174/1875399X01205010009

Davids, K., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach*. Human Kinetics. http://www.humankinetics.com/products/showproduct.cfm?

Farrow, D., & Robertson, S. (2017). Development of a skill acquisition periodisation framework for high-performance sport. *Sports Medicine*, *47*(6), 1043–1054. https://doi.org/10.1007/s40279-016-0646-2

Fleay, B., Joyce, C., Banyard, H., & Woods, C. (2018). Manipulating field dimensions during small-sided games impacts the technical and physical profiles of Australian footballers. *Journal of Strength and Conditioning Research*, *32*(7), 2039–2044. https://doi.org/10.1519/JSC.0000000000002423

Hodges, N. J., & Franks, I. M. (2002). Modelling coaching practice: The role of instruction and demonstration. *Journal of Sports Sciences*, *20*(10), 793–811. https://doi.org/10.1080/026404102320675648

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33* (1), 159–174. JSTOR https://doi.org/10.2307/2529310

McIntosh, S., Jackson, K. B., & Robertson, S. (2021). Apples and oranges? Comparing player performances between the Australian Football League and second-tier leagues. *Journal of Sports Sciences*, *39*(18), 2123–2132. https://doi.org/10.1080/02640414.2021.1921372

McIntosh, S., Kovalchik, S., & Robertson, S. (2018). Examination of player role in the Australian Football League using match performance data. *International Journal of Performance Analysis in Sport*, *18*(3), 451–462. https://doi.org/10.1080/24748668.2018.1486116

Morgan, S., Williams, M. D., & Barnes, C. (2013). Applying decision tree induction for identification of important attributes in one-versus-one player interactions: A hockey exemplar. *Journal of Sports Sciences*, *31*(10), 1031–1037. https://doi.org/10.1080/02640414.2013.770906

Newell, K. M. (1985). Coordination, control and skill. In D. Goodman, R. B. Wilberg, & I. M. Franks (Eds.), *Advances in Psychology* (Vol. 27, pp. 295–317). North-Holland. https://doi.org/10.1016/S0166-4115(08)62541-8

Newell, K. M. (1986). Constraints on the development of coordination. In M. Wade & H. Whiting (Eds.), *Motor Development in children: Aspects of coordination and control* (pp. 341–360). Martinus Nijhoff.

Newell, K. M., Liu, Y.-T., & Mayer-Kress, G. (2001). Time scales in motor learning and development. *Psychological Review*, *108*(1), 57. https://doi.org/10.1037/0033-295X.108.1.57

Orth, D., Kamp, J. V. D., & Button, C. (2019). Learning to be adaptive as a distributed process across the coach–athlete system: Situating the coach in the constraints-led approach. *Physical Education and Sport Pedagogy*, *24*(2), 146–161. https://doi.org/10.1080/17408989.2018.1557132

Pinder, R. A., & Renshaw, I. (2019). What can coaches and physical education teachers learn from a constraints-led approach in para-sport? *Physical Education and Sport Pedagogy*, *24*(2), 190–205. https://doi.org/10.1080/17408989.2019.1571187

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup. *European Journal of Sport Science*, *18*(10), 1309–1316. https://doi.org/10.1080/17461391.2018.1486459

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2021). Effects of manipulating specific individual constraints on performance outcomes, emotions, and movement phase durations in Rugby Union place kicking. *Human Movement Science*, *79*, 102848. https://doi.org/10.1016/j.humov.2021.102848

Pocock, C., Bezodis, N. E., North, J. S., North, J. S., & North, J. S. (2020). Understanding key constraints and practice design in Rugby Union place kicking: experiential knowledge of professional kickers and experienced coaches. *International Journal of Sports Science & Coaching*, *15*(5–6), 631–641. https://doi.org/10.1177/1747954120943073

R Core Team. (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Renshaw, I., & Chow, J.-Y. (2019). A constraint-led approach to sport and physical education pedagogy. *Physical Education and Sport Pedagogy*, *24*(2), 103–116. https://doi.org/10.1080/17408989.2018.1552676

Renshaw, I., Chow, J. Y., Davids, K., & Hammond, J. (2010). A constraints-led perspective to understanding skill acquisition and game play: A basis for integration of motor learning theory and physical education praxis?

Physical Education and Sport Pedagogy, *15*(2), 117–137. https://doi.org/10.1080/17408980902791586

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. https://doi.org/10.1080/02640414.2018.1555905

Teune, B., Spencer, B., Sweeting, A. J., Woods, C., Inness, M., & Robertson, S. (2021). Application of a continuous pressure metric for Australian football. *Journal of Sports Sciences*, *39*(13), 1548–1554. https://doi.org/10.1080/02640414.2021.1886416

Teune, B., Woods, C., Sweeting, A., Inness, M., & Robertson, S. (2021). The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. *European Journal of Sport Science*, *22*(8), 1268–1275. https://doi.org/10.1080/17461391.2021.1958011

Therneau, T., & Atkinson, B. (2022). *rpart: Recursive Partitioning and Regression Trees*. (R package version 4.1.16). The Comprehensive R Archive Network. https://CRAN.R-project.org/package=rpart

Timmerman, E. A., Savelsbergh, G. J. P., & Farrow, D. (2019). Creating appropriate training environments to improve technical, decision-making, and physical skills in field hockey. *Research Quarterly for Exercise and Sport*, *90*(2), 180–189. https://doi.org/10.1080/02701367.2019.1571678

Williams, A. M., & Ford, P. R. (2009). Promoting a skills-based agenda in Olympic sports: The role of skill-acquisition specialists. *Journal of Sports Sciences*, *27*(13), 1381–1392. https://doi.org/10.1080/02640410902874737

Woods, C. T., McKeown, I., Rothwell, M., Araújo, D., Robertson, S., & Davids, K. (2020). Sport practitioners as sport ecology designers: how ecological dynamics has progressively changed perceptions of skill "acquisition" in the sporting habitat. *Frontiers in Psychology*, *11*, 654. https://doi.org/10.3389/fpsyg.2020.00654

VICTORIA UNIVERSITY

THE NEW WAY TO DO UNI

OFFICE FOR RESEARCH TRAINING, QUALITY AND INTEGRITY

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)

Title of Paper/Journal/Book: The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training

https://doi.org/10.1080/02640414.2022.2124013

Surname: Teune First name: Ben

Institute: Institute for Health and Sport Candidate's Contribution (%): 75

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 22/09/2022

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]	29/11/2022
Signature	**Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

1. They meet criteria for authorship in that they have participated in the conception, execution or interpretation of at least that part of the publication in their field of expertise;
2. They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;

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

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

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 storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Carl Woods	5	Assisted with theoretical positioning, feedback and revisions	[redacted]	18/07/22
Alice Sweeting	5	Assisted with methodology, feedback and revisions		19/07/22
Mathew Inness	5	Assisted with feedback and revisions		26/07/22
Sam Robertsons	10	Assisted with concept and study design, feedback and revisions		27/07/22

Updated: September 2019

The influence of individual, task and environmental constraint interaction on skilled behaviour in Australian Football training

5.1 Abstract

An important consideration for sport practitioners is the design of training environments that facilitate skill learning. This study presented a method to determine individual (age, games played, height, mass, and position), environmental (activity type) and task (pressure and possession time) constraint interaction to evaluate player training behaviour, which can be used to inform training design. Skill actions (n=7301) were recorded during training activities (n=209) at a single professional Australian Football club and four measures of player behaviour were determined for each activity: disposal frequency, kick percentage, pressure and possession time. K-means clustering assigned training activities into four groups, with regression trees used to determine the interaction between constraints and their influence on disposal frequency and type. For most regression tree models, only the environmental constraint was included. This showed all players adapted similarly to the constraints of each training activity. In one exception, a critical value of 60 games experience was identified as an individual constraint which interacted with activity type one to influence disposal frequency. This individual constraint value could be used to inform training design by grouping similar players together. This study is presented as a practical tool for sport practitioners and coaches, which considers constraint interaction, to evaluate the performance of their players during training and inform the training design.

5.2 Introduction

An important consideration for sport practitioners relates to the design of training environments that can facilitate skill learning (Davids, 2012). Training, then, is an important component of the coaching process, especially in high performance sport (Hodges & Franks, 2002; Orth et al., 2019). Moreover, it is the design of game-like training tasks that are particularly important to support the development of an athlete's skill (Chow, 2013; Davids et al., 2008). What makes training design challenging, is that skill is an emergent phenomena that results from the various interactions of the person (i.e., the athlete), the environment they perform in, and the task they are undertaking (Araújo et al., 2006; Newell, 1986). In other words, it is a confluence of interacting constraints that shapes the emergence of skill, and the goal of the coach in training design, then, is to nudge or guide athletes towards useful movement and performance solutions (Woods, McKeown, Rothwell, et al., 2020).

The constraints-led approach (CLA) is a framework that can be used to help practitioners with the design of practice tasks (Davids et al., 2008; Renshaw et al., 2010). In this framework, constraints are understood as boundaries, which exist along multiple time-scales, that shape the emergent actions of individuals (Newell, 1986; Newell et al., 2001). Broadly, constraints are classified into one of three classes: task, environmental and individual (Newell, 1986). In sport, task constraints typically relate to the intent of an activity; what needs to be achieved and within what time. Environmental constraints include features external to the performer, such as ambient weather conditions, ground surface properties, and field size. Individual constraints pertain to characteristics of a performer, like anthropometric and physiological qualities, or emotional states and arousal levels.

In harnessing tenets of the constraints-led approach, practitioners can guide athlete behaviour through the careful manipulation of constraints in practice tasks (Renshaw et al., 2010; Renshaw & Chow, 2019). For example, reducing field size can increase the frequency of interceptions in soccer (Casamichana & Castellano, 2010), or manipulating a team outnumber can increase the frequency of passes to uncovered players in Australian Football (AF) (Bonney et al., 2020). The manipulation of key constraints encourages problem-solving and facilitates an athlete's exploration for movement solutions (Woods, McKeown, Rothwell, et al., 2020). Thus, to assist with athlete learning, the evaluation of constraint manipulations, and how they have shaped emergent behaviour, can be of use for sports practitioners (Teune, Woods, et al., 2021a).

A challenge for practitioners in evaluating athlete behaviour is that constraints do not function in isolation but interact, often non-linearly (Newell, 1985). Accordingly, constraint interaction is important to consider, to protect against the influence of a constraint being over or under valued when contextualised within larger constraint sets. This increases the complexity of implementing constraint manipulations during practice and understanding their combined influence. In field hockey, for example, the number of players (i.e., an environmental constraint) and the intent of the task, have been shown to interact, influencing the frequency of certain actions (Timmerman et al., 2019). Moreover, studies in AF have examined the multivariate interaction between task and environmental constraints to evaluate match play kicking performance (Browne, Sweeting, et al., 2019; Robertson et al., 2019a), goal kicking performance (Browne et al., 2022) and skilled behaviour during training activities (Teune, Woods, et al., 2021a). Together, this work demonstrates how considering the interaction of multiple constraints may garner more precise insights to support practice design. However, investigations of constraint interactions have mainly been limited to environmental and task constraint classes. To build upon this work, studies which include individual constraint interactions with environmental and task constraints are largely yet to be explored. One exception in Rugby Union modelled place kicking effectiveness using logistic regression including interaction between game time (environmental constraints), score margin (environmental constraint), previous kick success (individual constraint), distance (task constraint) and angle (task constraint) to goal (Pocock et al., 2018).

Multivariate analytical techniques which can consider non-linear constraint interaction are important to appropriately contextualise player behaviour (Browne et al., 2021). Some analytical techniques, such as rule induction or decision trees, have such capabilities and have been applied to constraint analysis in AF match play (Browne et al., 2022; Browne, Sweeting, et al., 2019;

Robertson et al., 2019a) and practice (Browne et al., 2020; Teune, Woods, et al., 2021a). Further, unsupervised machine learning techniques such as k-means clustering algorithms have been applied to AF practice to group training activities according to similarities in player performance (Corbett et al., 2018). Specifically, *k*-means clustering has been useful to identify associations between training activity design and player performance (Corbett et al., 2018). These techniques provide interpretable outputs that make them applicable for end users in sport, such as coaches. An adaptation of such techniques may be beneficial as a practical tool for practitioners to evaluate team sport training while considering constraint interaction between all three classes. Therefore, the aim of this study was to present a method to measure the relationship between interacting task, environmental and individual constraints on disposal frequency and kick percentage during AF training.

5.3 Methods

5.3.1 Participants

Participants were listed Australian Football League players (n = 54, height = 187cm ± 7.83, mass = 84.7 kg ± 7.73, age = 24.4 years ± 3.42) at a single club during the 2021-2022 seasons. All participants provided written informed consent and were injury free at the time of participation. Ethical approval was obtained from the University Ethics Committee (application number: HRE20-138).

5.3.2 Data Collection

Data were collected on 209 training activities, consisting of 34 different activity designs. All activities were characterised as a small sided game, where two teams competed against each other within a specified field of play. Each activity type varied in the task goals, rules, field size or number of players. Skill involvement data were collected via filming with a 25 Hz two-dimensional camera (Canon XA25/Canon XA20) from a side-on or behind-the-goals perspective. Skill involvements during each activity were coded via notational analysis software (Sportscode, version 12.2.10, Hudl) using a customised code window whereby each skill involvement (or “disposal”) was labelled according to the type (kick or handball) and the player’s name who performed the skill (n = 7301). Each disposal was further labelled with two task constraints: pressure (present or absent) and possession time (<2 s or >2 s). Pressure was defined as a disposal performed within 3 m of an opponent, while possession time was defined as the time between receiving and disposing the ball. Inter-rater reliability of the notational coding was assessed using a hold-out sample of 168 disposals, not included in the main analysis, resulting in a Kappa statistic (Landis & Koch, 1977) of “almost perfect” (>0.8) for all variables. Intra-rater reliability was conducted after a 14-day washout period resulting in Kappa statistics ranging from “substantial” (0.67-0.8) to “almost perfect” (>0.8) across three coders.

Individual constraints for each player were recorded at the beginning of each season which were height (cm), weight (kg), number of games played (#) and playing position (defender, midfielder, forward or key position). Age (years) was also determined as the time period between the player’s date of birth and the date of training activity occurrence. Playing positions were assigned in consultation with the club’s coaching staff who were familiar with individual player roles. Distributions of each individual constraint are shown in Figure 1. Skill involvement data was labelled with individual constraints according to the player’s name associated with each disposal. For every training activity, each player’s skilled performance was then summarised according to four measures: disposal frequency, kick percentage, pressure and possession time. Disposal frequency was calculated as the total disposals divided by the activity duration in minutes, while kick percentage was represented as the percentage of kicked disposals. Pressure was represented as the percentage of pressured disposals, and possession time was represented as the percentage of disposals < 2 s. These calculations resulted in 2499 individual training activity performances.

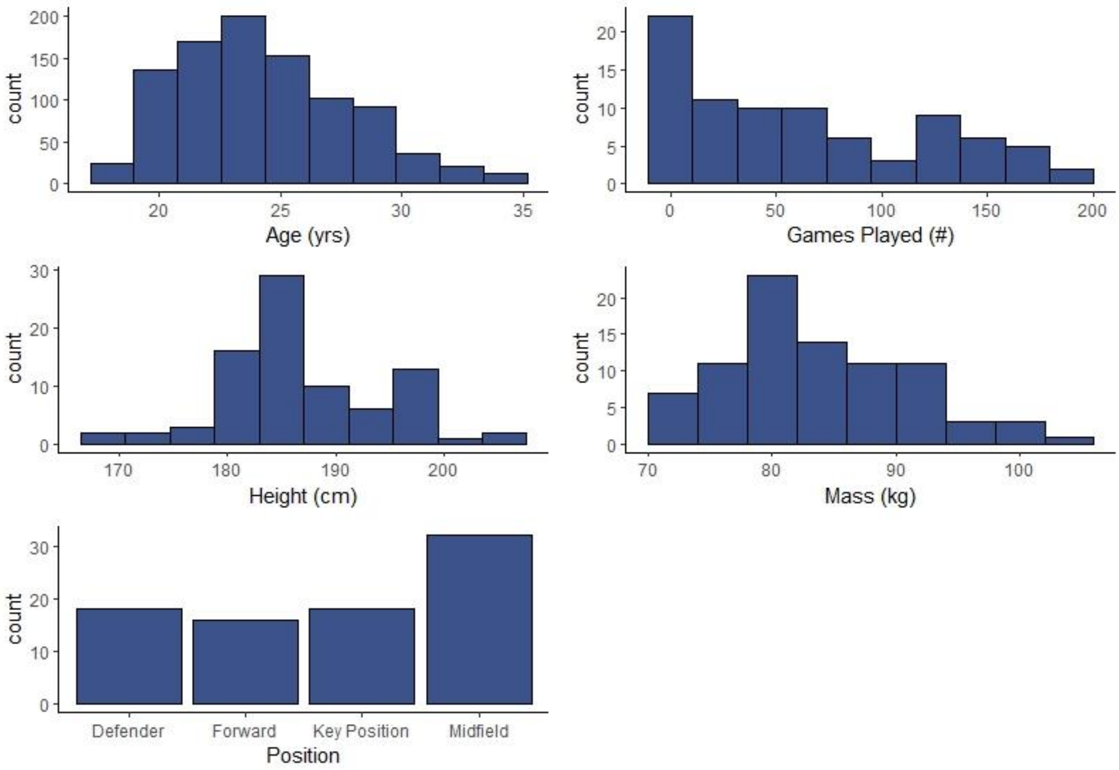


Figure 5.1 Distribution of each individual constraint included in analysis.

5.3.3 Statistical Analysis

To determine the influence of constraint classes, and their interactions, on player skilled behaviour, four analyses were conducted. This approach was taken to demonstrate the influence of constraint classes when considered both in isolation and in combination.

In the first analysis, to estimate the interaction between constraints, regression trees were used (Morgan et al., 2013). To determine the influence of individual constraints alone on player performance, two regression trees were grown, estimating disposal frequency and kick proportion, respectively. To determine the interaction between individual and task constraints, two further regression trees were grown to estimate pressure and possession time. All statistical analysis occurred in the R programming environment (R Core Team, 2019), with regression trees grown using the *rpart* package (Therneau & Atkinson, 2022). The five individual constraints were included as predictors in each of the models, and parameters were specified with a minimum split of 20 observations and a complexity parameter of 0.01.

In the second analysis, k-means clustering was used to identify the training activities which result in similar player outputs and were grouped accordingly to determine the influence of environmental constraints on skilled behaviour (Corbett et al., 2018). A scree plot was first generated to determine the appropriate number of clusters to use in analysis. 10 maximum iterations were permitted with, each training activity then assigned to one of the cluster memberships according to the results of the *k*-means clustering.

In the third analysis, to determine the interaction between environmental and individual constraint classes on skilled behaviour, regression trees were grown to estimate disposal frequency and kick percentage. Each of the five individual constraints and the environmental constraint of activity type, were included in the two models using the same parameters as previous models.

In the fourth analysis, to determine the interaction between environmental, individual and task constraint classes, two regression trees were grown to estimate pressure and possession time. The five individual constraints and the environmental constraint of activity type were included as predictors in the model. The same model parameters were used as previous models.

5.4 Results

Across 2499 training activities, the mean and standard deviation was 0.59 ± 0.46 disposals per minute, 60.2% ± 40% kicks, 40.7% ± 39.5% pressured disposals, and 51.2% ± 40% disposals <2 s. For the two regression tree models which included only individual constraints, the first estimated disposal frequency with a mean squared error of 0.22 disposals / min. The second model estimating kick percentage had a root mean squared error of 44.02 %. For the two regression trees which estimated task constraints using only individual constraints as predictors, the model estimating pressure had a root mean squared error of 39.49 % . The model estimating possession time had a root mean squared error of 39.98 %.

Visual analysis of the scree plot resulted in four clusters being selected. The four cluster centres resulting from the subsequent k-means clustering analysis is shown in Table 1. The distributions of the player performance metrics (disposal frequency, kick proportion, pressure and possession time) within each activity membership are shown in Figure 2. Cluster one was distinguished as handball only activities, with high levels of disposal frequency, pressure and lower possession times. Cluster two had the highest proportion of kicked disposals and disposals < 2 s and the lowest level of pressure. Cluster three had the lowest disposal frequency, a high proportion of kicks with low pressure and time constraints. While cluster four was similar to cluster one in terms of pressure and possession time, but involved predominantly kicked disposals with a lower disposals frequency.

Table 5.1 Cluster centres (averages) of each training performance metric for drill activity memberships

Cluster membership	Disposal Frequency (p/min)	% Kicked Disposals	% Pressured Disposals	% Disposals <2 s
1	1.11	0	61.6	66.0
2	0.69	82.0	21.3	79.4
3	0.39	78.5	28.3	33.8
4	0.45	69.5	76.2	53.0

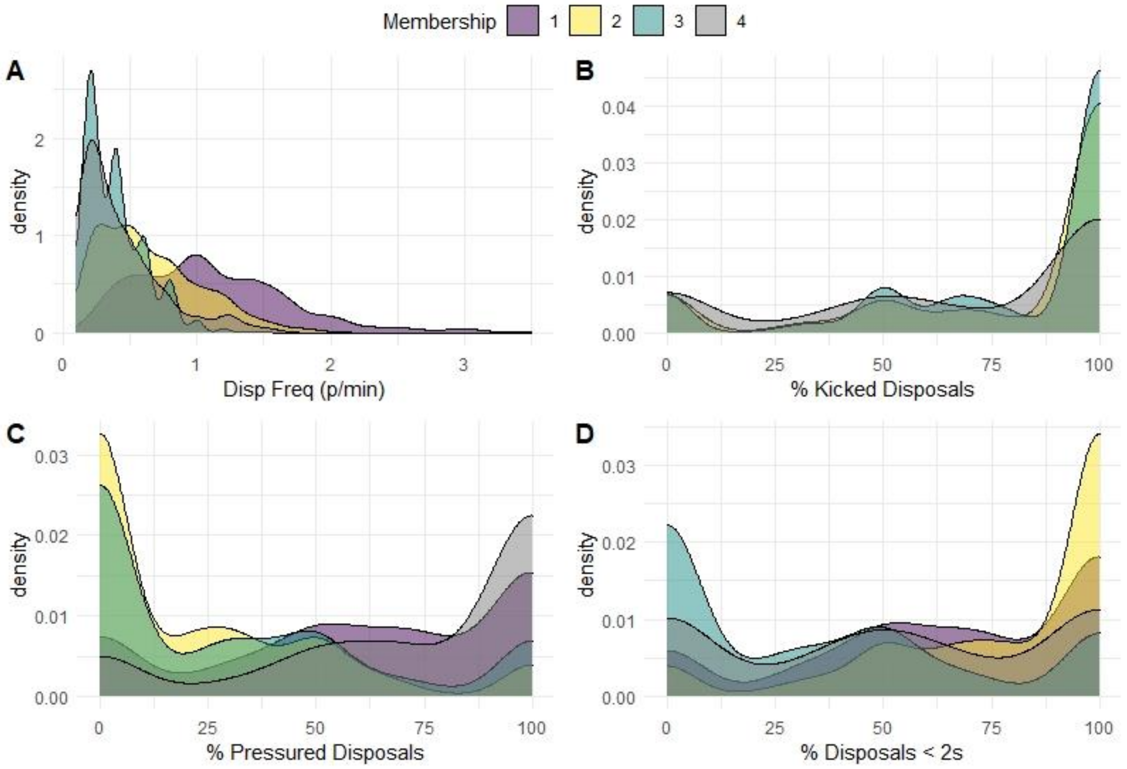


Figure 5.2 Distribution of training performance metrics; disposal frequency (A), kick percentage (B), pressure (C) and possession time (D) within each activity membership. Note, in panel B, data for cluster membership one has not been displayed given that no kicked disposals were recorded in this membership.

The regression trees that included environmental and individual constraints, estimating disposal frequency and kick percentage, are shown in Figures 3 and 4, respectively. The results of the tree estimating disposal frequency had a mean squared error of 0.129 disposals / min and an R squared value 0.40. Games played was the only individual constraint included in the model which was shown to positively influence disposal frequency for activities in membership one. The regression tree estimating kick percentage had a root mean squared error of 29.83 % and an R squared value of 0.54. No individual constraints were included in this model.

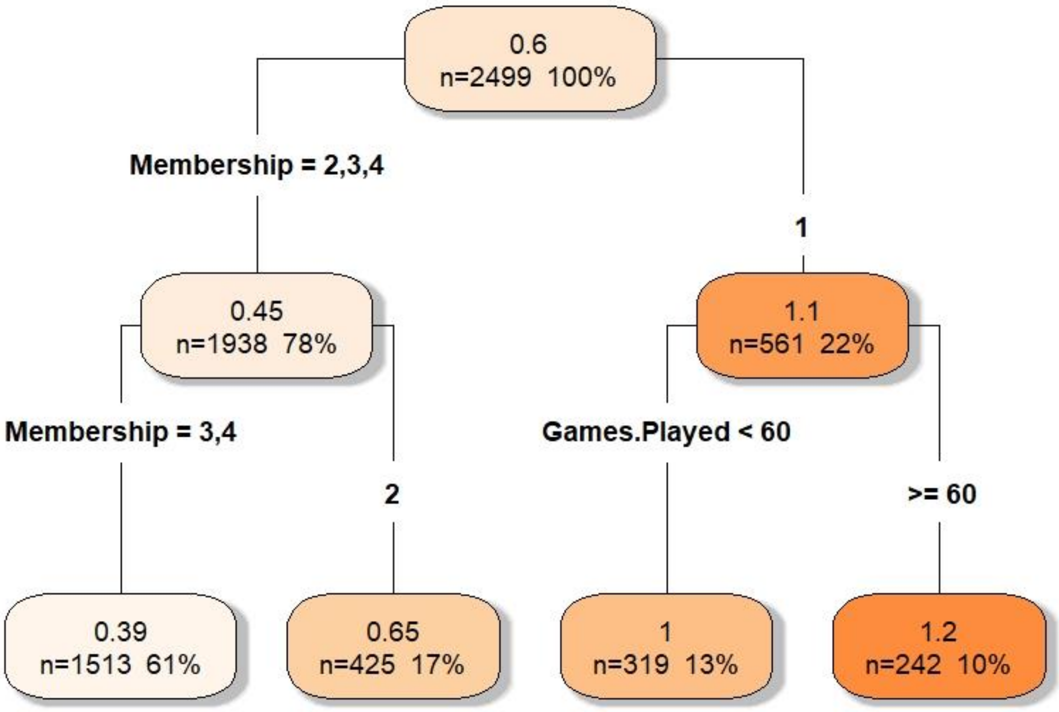


Figure 5.3 Regression tree modelling disposal frequency (disposals / min). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (disposals / min). The bottom values in each node represent the frequency and percentage of cases within each node.

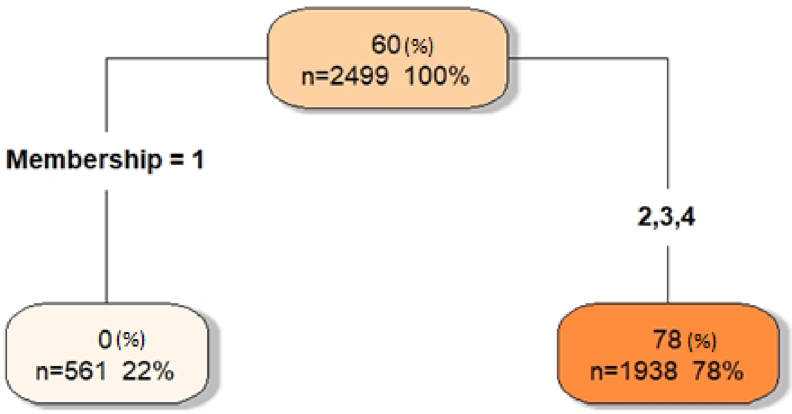


Figure 5.4 Regression tree modelling disposal type (% of kicked disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of kicked disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

The regression trees that included environmental and individual constraints, used to estimate task constraints, pressure and possession time, are shown in Figures 5 and 6, respectively. The results of the model estimating pressure had a root mean squared error of 34.69 % and an R squared value of 0.22. The model estimating possession time had a root mean squared error of 35.62 % and an R squared value of 0.21. Neither of these models included any individual constraints to partition the data.

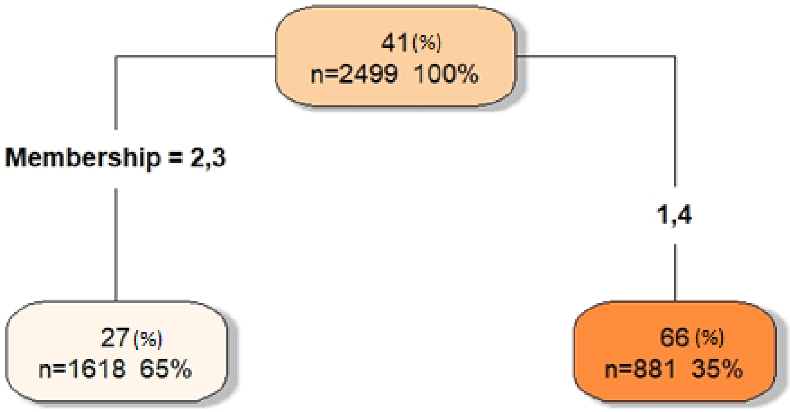


Figure 5.5 Regression tree modelling pressure (% of pressured disposals). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of pressured disposals). The bottom values in each node represent the frequency and percentage of cases within each node.

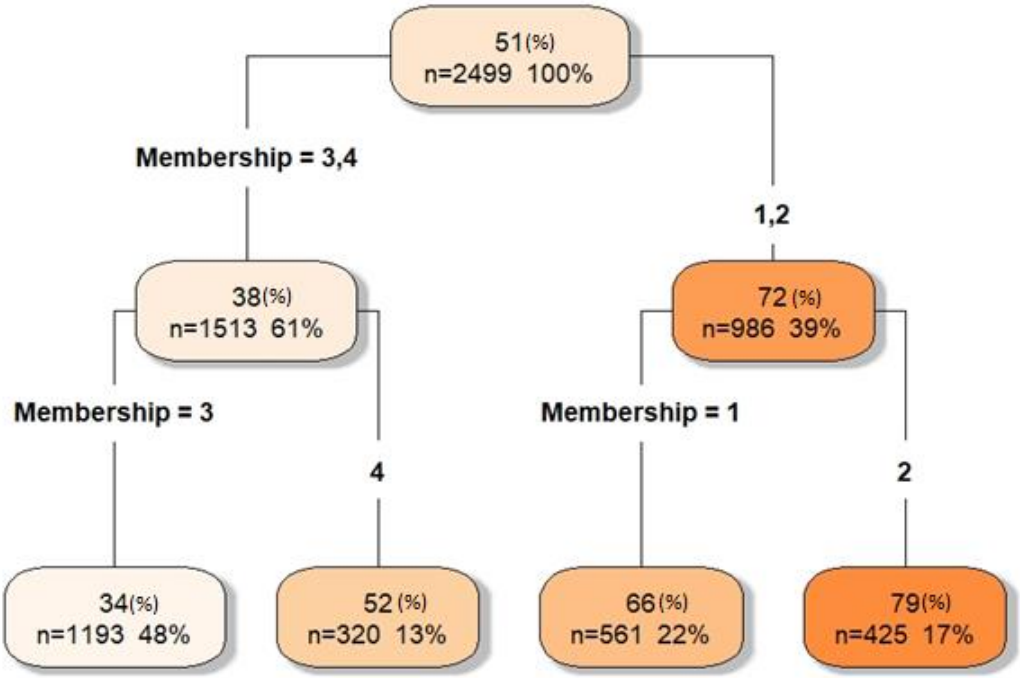


Figure 5.6 Regression tree modelling possession time (% of disposals < 2s). Environmental constraints (cluster memberships) and individual constraints (age, games played, height, mass, position) were included as independent variables. The top number reported in each node represents the estimated outcome value (% of disposals < 2s). The bottom values in each node represent the frequency and percentage of cases within each node.

5.5 Discussion

This study demonstrated a method to evaluate player performance in a team sport training environment by considering the interaction of individual, environmental and task constraints. Results showed that the environmental constraint of activity type was the most influential on player performance, indicating that players adapted their performance to suit the training activity design. The individual constraints collected in this study had limited influence on player performance, suggesting that coaches achieved activity designs that constrained player behaviour in a similar way, regardless of individual characteristics. In one exception however, games played showed an interaction with activity type one, suggesting that experienced players were better able to perform more disposals than less experienced teammates. Task and environmental constraint interaction was also demonstrated, indicating the environmental constraint of activity types influenced the levels of pressure and possession time however, the individual constraints collected in this study did not influence this.

Individual constraints, when considered alone, did not influence disposal frequency or kick percentage, nor did they influence the task constraints of pressure or possession time. This contradicts other work where individual constraints have been influential on skilled performance (Almeida et al., 2016; Cordovil et al., 2009; Pocock et al., 2018, 2021). This result may be explained by the wide range of varying activity types included in the current study, leading to variability in performance. Individual constraints are perceived by coaches as an important feature to consider in practice design (Pocock et al., 2020). However, these results indicate that there were no general trends in player performance which were applicable across all activity types. Further context to these constraints is required, thereby helping coaches evaluate player performance more effectively. This result may also mean that different or more sensitive, individual constraints need to be considered in future research, inclusive of physiological qualities or psychological attributes.

The *k*-means clustering was beneficial to determine associations between the practitioner's activity designs and player performance whereby, activities which result in similar player performances can be identified. For example, the activities included in cluster one were limited to handballs only and represented tasks with a rule constraint which did not permit kicking. Contrastingly, cluster two activities were designed with constraints which encouraged a high proportions of quick kicks with low levels of pressure. This suggests, within this group of activities, that players were able to identify passing options quickly and dispose of the ball before defensive pressure could be applied. K-means clustering could be helpful for activity prescription allowing coaches to select a range of activities from particular groups which meet certain training targets, such as a focus on kicking or performing disposals under pressure. Accordingly, coaches may use this to inform an approach which emphasises training design rather than direct instruction, to shape player behaviour and facilitate skill development (Woods, McKeown, Rothwell, et al., 2020). Additionally, the clustering approach is flexible to be applied to any team and across any parameters deemed important by practitioners.

Including the environmental constraint of activity type with individual constraints in the regression trees was able to improve the model's accuracy. This result was expected as activity type was previously grouped according to the player performance metrics. However, the individual constraints included in the models had limited capacity in explaining further variance within each activity type. This result highlights the capability of the coaches to design activities that constrain player performance similarly. Thus, the minimal influence of individual constraints is a beneficial insight for practitioners, identifying the consistent influence of their activity design across all players, regardless of individual characteristics. In one exception, an interaction between activity type one and games played influenced disposal frequency. According to the cluster centres, activity type one was characterised as a fast game with high disposal frequency using all handballs, high levels of pressure and high levels of temporal constraints. Accordingly, within this group of activities, experience was important in shaping how often a player performed a disposal. This may be due to the higher skill of experienced players to perform under the high temporal and pressure constraints, positioning themselves more optimally to receive and dispose the ball. Alternatively, experienced players may be more frequently sought out by teammates as passing options. Importantly, the model identified a critical value for experience of 60 games, which may be leveraged by coaches to inform individual differences in performance during this activity type. In this case, players could be divided into "more experienced" (> 60 games) and "less experienced" (< 60 games) groups. Coaches may utilise this grouping to achieve their training goals, purposefully accelerating the skill development of less experienced players by placing them against more experienced ones. Alternatively, less experienced players may train against other less experienced players, potentially increasing their disposal frequency and providing them with more learning opportunities. Less experienced players could also be provided additional training activities after the session, or the activity could be run for longer to allow these players to accrue more disposals. This result exemplifies how the analysis can be practically implemented to assist a coach's ability to structure and plan training sessions while considering important individual differences (Chow, 2013).

The environmental constraint interacted with the two task constraints of pressure and possession time however the regression trees were only able to explain 22% and 21% of the variance in these constraints, respectively. This indicated that these constraints were highly variable within activity types and may be a result of constraint manipulations implemented by coaches which were not collected in this study. For example, field dimension or the number of players may have been manipulated from session to session, according to changes in player availability or to directly influence player performance. Indeed, field dimension and the number of players has been shown to influence player performance in AF (Bonney et al., 2020; Fleay et al., 2018; Teune, Spencer, et al., 2021; Teune, Woods, et al., 2021a). In the present study, only the environmental constraint was shown to influence the task constraints, with none of the individual constraints included in the resulting models. Accordingly, alternate or improved measures of individual constraints may need to be collected to determine their influence on player performance. For example, players were allocated into one of four positions; forward, midfield, defender or key position. However, unlike some sports, such as netball, the nature of positions in AF is dynamic. More detailed position groupings may influence the models such as including small general forwards and defenders, or rucks, as used in other AF work (McIntosh et al., 2018a).

Given the applied nature of the current study, there are limitations that require recognition. First, specific constraints such as field dimensions, number of players or task rules were not collected. This could have been manipulated by coaches between sessions and may therefore have influenced behaviour. Additionally, environmental constraints, like fluctuations in wind, rain, ambient temperature or time in session of practice task were not collected, which may have influenced player performance. Finally, given the broad time range in which data collection occurred, it is possible that player performance adapted over time according to changes in tactical directions of coaching staff. Thus, future work may benefit from measuring training performance adaptations over longitudinal timelines to inform training design (Farrow & Robertson, 2017).

5.6 Conclusion

This study developed a method to measure interaction between individual, environmental and task constraints during AF training. The environmental constraint, activity type, was the most influential on individual training performance highlighting the achievement of coaches to design training which constrains all players similarly. The individual constraint of player experience interacted with one activity type. It was shown how the analysis can be used to identify critical constraint values, such as 60 games played, which can inform training design by allocating players into specific groupings. This study is presented as a practical tool for sport practitioners and coaches to evaluate the performance of their players during training and inform the design and structure of training activities.

CHAPTER SIX – STUDY IV

Chapter Overview

Chapter Six is the fourth of five studies contained in this thesis. While Chapters Two and Three supported sport practitioners in their evaluation and design of training activities, Chapter Six explores how to inform the duration of such activities. This builds upon the previous chapters by addressing an additional component of training prescription and by integrating a measure of the athlete's physical output, Specifically, this study investigates how univariate and multivariate change point detection may be applied to inform activity duration in AF.

The content of this chapter is an accepted manuscript of an article published by PLoS Journals in PLoS ONE on 21st March 2022, available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0265848

PLOS ONE

RESEARCH ARTICLE

A method to inform team sport training activity duration with change point analysis

Ben Teune[1,2☯*], **Carl Woods**[1‡], **Alice Sweeting**[1,2‡], **Mathew Inness**[1,2‡], **Sam Robertson**[1‡]

1 Institute for Health and Sport (iHeS), Victoria University, Melbourne, Australia, **2** Western Bulldogs, Melbourne, Australia

☯ These authors contributed equally to this work.
‡ These authors also contributed equally to this work.
* benteune@outlook.com

OPEN ACCESS

Citation: Teune B, Woods C, Sweeting A, Inness M, Robertson S (2022) A method to inform team sport training activity duration with change point analysis. PLoS ONE 17(3): e0265848. https://doi.org/10.1371/journal.pone.0265848

Editor: Shazlin Shaharudin, Universiti Sains Malaysia, MALAYSIA

Received: October 20, 2021

Accepted: March 8, 2022

Published: March 21, 2022

Data Availability Statement: All relevant data are within the paper and its Supporting information files.

Funding: The authors received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist. The affiliation of authors BT and MI to the Western Bulldogs does not alter the authors adherence to PLOS ONE policies on sharing data and materials.

Abstract

Duration is a key component in the design of training activities in sport which aim to enhance athlete skills and physical qualities. Training duration is often a balance between reaching skill development and physiological targets set by practitioners. This study aimed to exemplify change point time-series analyses to inform training activity duration in Australian Football. Five features of player behaviour were included in the analyses: disposal frequency, efficiency, pressure, possession time and player movement velocity. Results of the analyses identified moments of change which may be used to inform minimum or maximum activity durations, depending on a practitioner's objectives. In the first approach, a univariate analysis determined change points specific to each feature, allowing practitioners to evaluate activities according to a single metric. In contrast, a multivariate analysis considered interactions between features and identified a single change point, reflecting the moment of overall change during activities. Six iterations of a training activity were also evaluated resulting in common change point locations, between 196 and 252 seconds, which indicated alterations to player behaviour between this time period in the training activities conduction. Comparisons of feature segments before and after change points revealed the extent to which player behaviour changed and can guide such duration decisions. These methods can be used to evaluate athlete behaviour and inform training activity durations.

Introduction

Sport practitioners often use games-based training activities, or drills, to facilitate the development of physiological capacities and skill qualities of team sport athletes [1, 2]. A key component of the design of such training activities relates to their duration, with practitioners needing to consider the appropriate time for skill learning to occur, while balancing physiological targets needed to improve performance and minimise injury risk [3]. When evaluating training duration, contextualising player behaviour as a function of time provides more detailed insights into how and why certain outcomes have occurred [4]. For example, Australian football (AF) players reduce aggregate physical and technical performance following periods of peak physical intensity in match play [5] or during the second half of match play [6]. In football, second half physical activity is influenced by first half activity levels [7]. Accordingly, such insights allow training to be designed more specifically to player activity levels. Suitable time sensitive data analyses may help inform training duration by providing measures of the fluctuation of player behaviour during training activities, which may indicate a decline in the efficacy of the aims of a particular activity. However, specific techniques to achieve this have not yet been applied to support training prescription.

To inform and evaluate training in team sports, data are typically collected from multiple sources, such as player tracking devices or manual annotation. Commonly, these data are reported using aggregate measures such as distance run, average speed or the volume of skill executions [1, 2]. Such measures have also been compared with aggregate match data to determine the extent to which training activities reflect match demands [1, 8, 9]. However, aggregate measures remain limited in utility as they do not represent the fluctuation of such measures as a function of time. In attempts to alleviate this, player speed has been analysed during matches as subsets of varying time periods such as rolling (between one and ten minutes) time windows [10], five-minute blocks [11], sub-phases of play [12] or player on-field stints [13].

Analyses of measures in a continuous format may yield further detailed insights. The use of continuous measurement is further supported by the framework of the constraints-led approach [14]. This framework conceptualises constraints, such as pressure and time, as boundaries of the performer-environment system which shape the emergence of skilled behaviour. Specifically, constraints emerge and decay over varying time scales, and capturing this change over time is crucial in understanding and contextualising athlete behaviour [15, 16]. Accordingly, a continuous time-series analysis, which evaluates changing contextual information and identifies when meaningful change has occurred, could be beneficial in informing training durations.

Change point detection, also known as time series segmentation, is an analytical method of determining specific locations in a time-series when a meaningful change has occurred. This algorithm can be used to detect single or multiple change points and has been widely applied in areas such as medical monitoring and climate change detection [17]. In sport, change point detection has been applied in AF match play to segment player velocity data to identify potential interchange moments [18]. Recent advances to change point detection can also now perform multivariate analysis [19]. In this approach, multiple sequences of data are combined to form a single time series with multiple observations, which allows for the detection of change points common across multiple time series [19]. Multivariate change point detection may be beneficial in sport where multiple sources of data can be integrated to evaluate a single activity [4, 20]. For example, athlete physical and skilled behaviour could be analysed together to detect moments of change within specific team-sport training activities. This may inform activity duration by objectively identifying when skilled and/or physical behaviour deviates meaningfully from specific training objectives. Thus, this study aimed to apply change point analysis as a method to inform team sport training activity duration, exemplified in AF.

Methodology

Participants

Participants were a convenience sample of listed players from a single professional AF club (n = 43; 84 ± 8.2 kg; 187 ± 8.1 cm; 24.5 ± 3.6 y). All players were injury free at the time of participation. Ethics approval was obtained from the Victoria University Human Research Ethics Committee (application number: HRE20-138). Written consent was provided by the club to use de-identified data collected as regular procedure during practice.

Data collection

Data were collected during the 2021 Australian Football League pre-season. Through consultation with coaching staff and the literature [1, 21], five features of player behaviour were identified to evaluate a training activity (disposal frequency, efficiency, pressure, player possession time and player velocity). Skill event data and player tracking data were collected for each training activity repetition (n = 6) as it occurred during regular pre-season training sessions. The training activity was a small sided game with even teams, with each team being required to score at opposing ends of the ground. Each repetition ranged from ten to twelve players per team, depending on player availability, with a field area of approximately 90 x 60 m and a minimum duration of four minutes. For each activity repetition, team selection was quasi-randomised by coaching staff to standardise player positions and skill level. Typical AF rules were governed during the activities by a single coach.

To determine velocity during each training activity repetition, each participant wore a 10 Hz Global Positioning System device (Vector S7, Catapult, Catapult Sports Ltd, Melbourne) placed on their backs between their shoulder blades. Each participant wore the same device during all activities to reduce inter-unit error. Upon completion of the training sessions, tracking data was downloaded for each activity using the associated software package (Openfield, v3.3.0). The tracking data comprised a velocity measurement at each 10 Hz timestamp, for each player and activity, before being subsequently exported for analysis.

All data analysis was completed using the *R* programming language with the *RStudio* software [22] (version 1.3.1093). Velocity data was down sampled to a rate of 1 Hz, by calculating the mean velocity across every 10 fixed samples. This sample rate was used to simplify the merging process with skill event data. To determine the movement velocity during each activity repetition, the average velocity across all players was calculated at each 1 Hz timepoint.

To collect the skill event data, each training activity repetition was filmed with a two-dimensional camera (Canon XA25/Canon XA20) at 25 Hz from a side on or behind the goal perspective. After the training sessions, notational software (Hudl Sportscode, v12.2.44) was used to manually quantify the skill event data. A custom code window was used to record each kick or handball (a "disposal") according to its type (effective or ineffective) and two constraints on the disposal; possession time (<2 s or >2 s) and physical pressure (pressure or absent). Effectiveness was defined in accordance with Champion Data (Melbourne, Pty Ltd), where a handball or kick <40 m was deemed effective, if the intended target retained ball possession. A kick >40 m was deemed effective if kicked to a 50/50 contest or outnumber to the advantage of the attacking team. Possession time was defined as the time period between a player's ball possession gain and the moment of ball disposal. Pressure was defined as the physical presence of an opposition player within 3 m of the ball-carrier at the time of ball disposal. Two coders notated effectiveness and three coders notated the constraints (pressure and possession time). To assess the reliability of the notational coding, 168 disposals across three activities—observations not used in analysis—were selected for testing. The Kappa statistic [23] resulted in "almost perfect" inter-rater reliability for each variable (>0.8). Intra-rater reliability testing was completed after 14 days which resulted in Kappa statistics ranging from "substantial" (0.67–0.8) to "almost perfect" across all coders (>0.8). All skill event data was then exported with a time-of-day timestamp rounded to the nearest second.

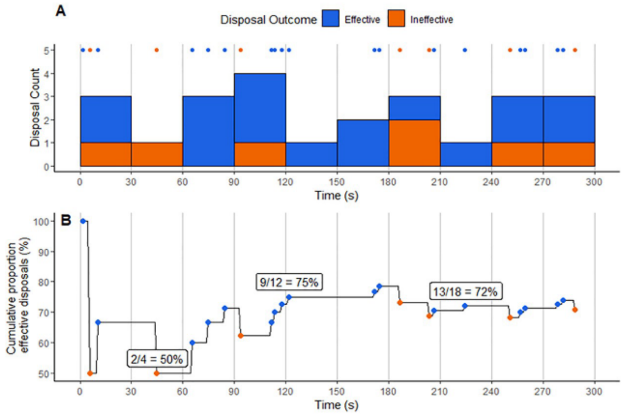


Fig 1. Example from a single activity repetition displaying disposal efficiency represented in 30 s bins (A) and continuously (B). Effective and ineffective disposal events are represented by the points. Three periodic annotations are provided to help describe the sequence calculation in panel B.

https://doi.org/10.1371/journal.pone.0265848.g001

For each training activity repetition, the skill event data was joined with the velocity data according to the timestamp. The first and last disposal marked the beginning and end of each activity repetition and was used to determine a relative timestamp in the dataset where each repetition began at zero seconds. To determine disposal frequency as a time series, a rolling sum was applied using a 60 s window. This was achieved using the *rollsum* function from the *zoo* package [24]. A 60 s window was selected as practitioners commonly prescribe activity durations in whole minutes and this function would evaluate a metric analogous to those commonly reported (e.g. metres per minute) in physical training literature [5, 6]. To determine efficiency as a time series, the proportion of cumulative effective disposals to cumulative total disposals was represented as a moving percentage over time. To determine pressure as a time series, the proportion of cumulative pressured disposals to cumulative total disposals was represented as a moving percentage over time. To determine possession time as a time series, the proportion of cumulative disposals with <2 s possession time to cumulative total disposals was represented as a moving percentage over time. This process resulted in four sequences to describe the skilled behaviour during each training activity: disposal frequency (p/min), efficiency (%), pressured disposals (%) and disposals <2 s (%). As an example, efficiency is represented via binning (Fig 1a) and as a continuous series via the above methods (Fig 1b) to contrast the effect of the time series conversion.

Statistical analysis

To estimate the time point during the activities when properties of the time-series change for each feature, the *cpt_mean* function from the *changepoint* package was used [25]. This function identifies the time point in a sequence where an abrupt change in the sequence mean occurs. The method chosen was AMOC (at most one change) which specifies the algorithm to search for a maximum of one change point in the sequence. This was specified due to the short duration of activities and for feasibility reasons for the end user. The change point algorithm was applied to the sequences of each of the five features for each activity. Each sequence was subsequently segmented according to its change point location.

To determine a single time location common for all features during each activity repetition, a multivariate change point analysis was performed [19]. To achieve this the *mrc* function from the *Changepoint.mv* package was used [26]. This function determines common change point locations across multiple sequence inputs of the same length. The features of each training activity were normalised to allow comparison across different measures. The *mrc* function was applied across the normalised feature sequences for each activity. The function parameters were set where the cost was "mean", specifying the algorithm to search for a change in the sequence means, and the maximum number of change points to search for was set to one. This parameter was chosen to locate a single change point common across all five features of the activity. Each activity was then segmented according to the identified multivariate change point location.

Results

Descriptive statistics are are presented as means and standard deviations. Across six repetitions of the training activity, the mean duration was 298 ± 17 seconds, disposal frequency was 5.7 ± 1.1 disposals/min, efficiency was 79.5 ± 9.1%, pressure was 40.6 ± 16.3%, possession time was 27.5 ± 19.6% and velocity was 127 ±.7.2 m•min^{-1}. The total number of skill involvements and activity duration included in the sample was 185 and 29.2 minutes, respectively.

To demonstrate the univariate and multivariate change point analysis approach, the results for a single activity repetition are reported in Figs 2 and 3, respectively. The left-hand column of panels visualises when the change points occurred and the right-hand column of panels visualises the feature distribution, before and after the change point, to describe the extent of change. The univariate change point analysis of disposal frequency, efficiency, pressure, possession time and velocity resulted in change point located at 85, 172, 124, 64 and 135 s respectively (Fig 2). For each feature the mean and standard deviation of the segments, before and after the changepoint, are reported in Fig 4. The multivariate changepoint approach resulted in a single changepoint for all skill features located at 204 seconds (Fig 3). For each feature the mean and standard deviation of the segments, before and after the changepoint, are reported in Fig 4.

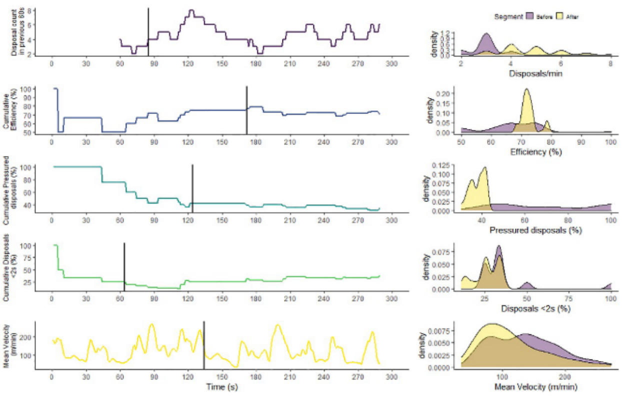


Fig 2. A univariate changepoint analysis of a single training activity. The left-hand column of panels displays the feature and the calculated changepoint location (black vertical line). The right-hand column of panels displays the distribution of the feature in each segment, before and after the changepoint.

https://doi.org/10.1371/journal.pone.0265848.g002

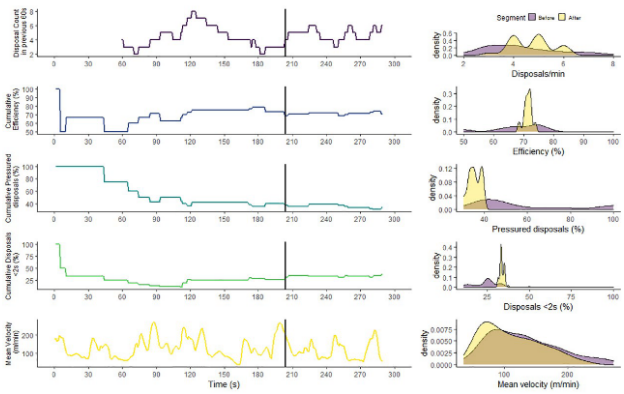


Fig 3. A multivariate changepoint analysis of a single training activity. The left-hand column of panels displays the feature and the calculated changepoint location (black vertical line). The right-hand column of panels displays the distribution of the feature in each segment, before and after the changepoint.

https://doi.org/10.1371/journal.pone.0265848.g003

To inform activity duration, the results of the multivariate changepoint analysis on each activity repetition was visualised in Fig 5. Change point locations occurred at 196, 203, 205, 210, 219 and 252 s. Across six repetitions the mean location was 214.2 s with a standard deviation of 20.1 s.

Discussion

This study presented a univariate and multivariate approach to determining change points during training activities that could be utilised by practitioners to inform training duration. Results demonstrated that the univariate approach was advantageous for providing

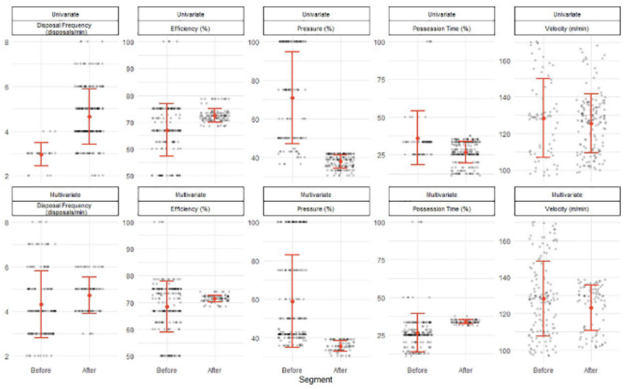


Fig 4. Summary statistics for segmented features according to a univariate and multivariate change point analysis of a single training activity. The orange point and error bars display the mean and one standard deviation of the segment, respectively. The black points each represent one second of the underlying segmented feature.

https://doi.org/10.1371/journal.pone.0265848.g004

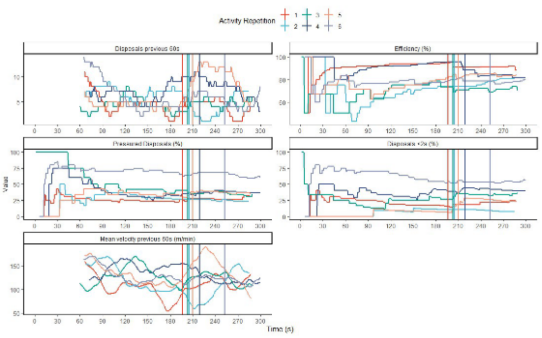


Fig 5. The sequences and multivariate changepoint locations for each feature of six activity repetitions. The feature value through the duration of the activity is displayed with straight vertical lines indicating a change point location. For velocity, the rolling mean over the previous 60 s is displayed to improve its visual interpretability. Feature sequences and changepoint locations are coloured according to activity repetition.

https://doi.org/10.1371/journal.pone.0265848.g005

information specific to each activity feature, which is useful for evaluating training according to a single metric. Comparatively, the multivariate approach is advantageous in analysing the interaction between multiple data sources, providing a simple output for the end user to inform a moment of overall change in the training activity. To guide informed activity duration decisions, visualisations were provided, summarising the univariate change point analysis of six repetitions of the training activity.

In the application of a univariate change point analysis, each of the five features were analysed separately. By resolving the change point location of each feature, a practitioner can identify when each feature meaningfully changed. To know the magnitude of change, the descriptive statistics comparing segments before and after the changepoint are shown in Fig 4. Fig 2 provides an example visualisation which may be useful for practitioners, displaying both when and to what extent each feature has changed during the activity.

According to key ideas of the constraints-led approach, player behaviour is continuously shaped under the interaction of various constraints [14]. The change point analysis used here may, therefore, help practitioners identify periods of behavioural change in a continuous manner. For example, the change point for pressure was identified at 124 seconds, reducing the mean and standard deviation by 33.1% and 20.5%, relatively, after this point (Fig 4). A potential explanation for this observation is the effect of fatigue, which can impact a defending player's capacity to physically pressure the ball-carrier. Thus, it is possible that defenders may have adapted how they defended—deciding to cover or protect space, rather than chasing the ball-carrier. In this case, the change point could be used to identify how a new behavioural pattern has emerged, which can inform a practitioner's decisions regarding training design and duration in future iterations of the activity. Indeed, research has measured the aggregate influence of constraints, such as field area [27], game type [28] or playing number [29] on physical and technical behaviour, however this relationship as a function of time presently remains unknown.

Determining a change point for each feature separately does have practical importance, allowing an activity to be evaluated according to a specific metric. For example, if a practitioner is seeking to ensure the efficiency of skills during a practice task does not drop below a certain level, a change point may be useful for noting when a meaningful shift has occurred, thereby allowing them to affect the design of the task. Further, univariate change point analysis has the potential to benefit practitioners with varying responsibilities, such as a conditioning coach and a skills coach. A conditioning coach, for example, can examine the change point for velocity to monitor the physiological demands on the players, while the skills coach can examine the change point for efficiency to monitor the difficulty of the task. This analysis provides a platform for collaboration between coaches to inform the duration of training that provides adequate time to achieve both physiological and skill targets. Importantly, although analysis has occurred separately, each of the features can still be visualised together (Fig 2), further encouraging collaboration between staff when evaluating the activity [20].

The multivariate change point approach analysed the interaction between features and identified one change point common across all features at 204 seconds (Fig 3). In the field, this approach provides a relatively simple output for practitioners, guiding decisions about practice design informed by a "general" or "overall" change point. As shown in Fig 4, the standard deviations of each feature after the change point were reduced. The larger variability of behaviour before the change point may, therefore, indicate exploratory actions of players searching for a stable solution suitable to the constraints of the task [30]. Depending on the practitioner's objective for the activity, the identified change point may then serve as a potential "cut-off" point for facilitating exploratory player behaviour or a "minimum duration" required to provide adequate time for players to attune to their environment. Thus the change point can serve to analyse acute changes in the learning process to inform training design however, these should be considered within the longer time-scales of the learning process, such as weeks and months [31].

To further support a practitioner's decision making regarding practice design, six iterations of the same activity were analysed, in a multivariate manner, to evaluate trends in their change points. The visualisation in Fig 5 presents an exemplar technique to communicate information to practitioners on change point locations and feature values during each activity repetition. Five of the six change points appear similar across each repetition (Fig 5). From a practice design perspective, this gives practitioners confidence that during this period there is a change in overall player behaviour. This may serve as a more optimal activity duration to prescribe during future iterations of the activity, reducing time spent in undesired behavioural states. Importantly, variable behavioural states are likely to occur during match play and may reflect a training target for practitioners. The analysis may then aide to increase the efficiency of training sessions by saving valuable training time. In Fig 5, each activity repetition has been colour-coded so practitioners may identify specific results, such as an outlier, if desired. Retrospective inspection of video footage may provide additional information (e.g. weather or player injuries) which may assist in explaining the result.

An important practical aspect of change point analysis is that it accepts various metric representations, such as a rolling mean for disposal frequency and continuous velocity data from player tracking devices. This increases versatility in an environment, such as sport, where multiple data types are common. Specifying the algorithm to search for one change point provides a simple "before" and "after" summary of the data which improves the interpretability for practitioners. Moreover, as the advancement of technology continues in sport, the implementation of an on-line change point analysis could provide further benefits to practitioners, which could be applied to provide real-time feedback during an activity. This could identify the moment a behavioural change occurs to signal the end of an activity rather than relying on a predetermined time. Alternatively, the change point may present a critical moment for practitioner intervention during a practice task. For example, certain constraints could be manipulated to perturb or preserve the efficiency of disposals during a practice task, such as introducing number imbalances to make it easier or harder for a team's offence. This may be used to disrupt the players transition into a stable state, encouraging further exploration, or can nudge the players towards more optimal stable solutions [32]. Irrespective, this analysis demonstrates how empirical and experiential knowledge of practitioners can be blended, exhibiting a balanced interaction between "man and machine" [33], while still preserving the domain specific expertise of practitioners [34].

Due to the applied nature of this research, there are some limitations. Only four skill features and one physical feature were collected. To increase to the understanding of player behaviour over time, other features, like target pressure, kick distance, high-speed running or sprint frequency could be included. Additionally, parameters for the change point analysis were set to search for one change point. Thus, future work could investigate the impact of multiple change points in analysing behaviour fluctuations during training activities. While a 60 s window was applied to determine disposal frequency, future work could investigate the influence of other rolling windows on the stability of this metric. Further, future work could explore change point analysis between athletes to account for potential individual differences which may exist. This may support the design of player-specific training durations, information which would be of use to conditioning and medical staff when re-integrating players into team training following injury. Finally, increasing the number of activity iterations presented here from six may help alleviate potential confounding factors of results, such as fluctuating weather conditions or teams.

Conclusion

This study applied a univariate and multivariate change point analysis to inform training duration. The univariate approach provided change points for each feature, information that would be beneficial for practitioners seeking specific guidance on the evaluation of key metrics to inform the duration of training activities. The multivariate approach provided a single time point of general change and may be broadly indicative of players transitioning into different behavioural states. Evaluating multiple repetitions of the same activity is useful for finding trends in behavioural change and can identify critical points during an activity which can guide decisions around activity duration or even constraint manipulation. Given the practicality of the results presented here, practitioners are encouraged to adapt similar analyses to inform their own training designs.

Supporting information

S1 Data. Skill event data and de-identified player velocity data.
(ZIP)

Author Contributions

Conceptualization: Ben Teune, Sam Robertson.

Data curation: Ben Teune.

Formal analysis: Ben Teune.

Methodology: Ben Teune, Sam Robertson.

Supervision: Carl Woods, Alice Sweeting, Mathew Inness, Sam Robertson.

Visualization: Ben Teune, Alice Sweeting.

Writing – original draft: Ben Teune.

Writing – review & editing: Ben Teune, Carl Woods, Alice Sweeting, Mathew Inness, Sam Robertson.

References

1. Corbett DM, Bartlett JD, O'connor F, Back N, Torres-Ronda L, Robertson S. Development of physical and skill training drill prescription systems for elite Australian Rules football. Sci Med Footb. 2018 Jan 2; 2(1):51–7.
2. Gabbett T, Jenkins D, Abernethy B. Game-Based Training for Improving Skill and Physical Fitness in Team Sport Athletes. Int J Sports Sci Coach. 2009 Jun 1; 4(2):273–83.
3. Vickery W, Nichol A. What actually happens during a practice session? A coach's perspective on developing and delivering practice. J Sports Sci. 2020 Jul 29; 38(24):2765–73. https://doi.org/10.1080/02640414.2020.1799735 PMID: 32723022
4. Glazier PS. Towards a Grand Unified Theory of sports performance. Hum Mov Sci. 2017 Dec 1; 56:139–56. https://doi.org/10.1016/j.humov.2015.08.001 PMID: 26725372
5. Black GM, Gabbett TJ, Naughton GA, McLean BD. The effect of intense exercise periods on physical and technical performance during elite Australian Football match-play: A comparison of experienced and less experienced players. J Sci Med Sport. 2016 Jul 1; 19(7):596–602. https://doi.org/10.1016/j.jsams.2015.07.007 PMID: 26315892
6. Black GM, Gabbett TJ, Naughton G, Cole MH, Johnston RD, Dawson B. The Influence of Contextual Factors on Running Performance in Female Australian Football Match-Play. J Strength Cond Res. 2019 Sep; 33(9):2488–95. https://doi.org/10.1519/JSC.0000000000002142 PMID: 28704310
7. Sparks M, Coetzee B, Gabbett JT. Variations in high-intensity running and fatigue during semi-professional soccer matches. Int J Perform Anal Sport. 2016 Apr 1; 16(1):122–32.
8. Browne PR, Woods CT, Sweeting AJ, Robertson S. Applications of a working framework for the measurement of representative learning design in Australian football. PLOS ONE. 2020 Nov 30; 15(11): e0242336. https://doi.org/10.1371/journal.pone.0242336 PMID: 33253204
9. Ireland D, Dawson B, Peeling P, Lester L, Heasman J, Rogalski B. Do we train how we play? Investigating skill patterns in Australian football. Sci Med Footb. 2019 Oct 2; 3(4):265–74.
10. Clarke AC, Whitaker M, Sullivan C. Evolving peak period, match movement, and performance demands in elite women's Australian football. J Sci Med Sport. 2021 Jul 1; 24(7):683–8. https://doi.org/10.1016/j.jsams.2021.01.006 PMID: 33531273
11. Carling C, Dupont G. Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? J Sports Sci. 2011 Jan 1; 29(1):63–71. https://doi.org/10.1080/02640414.2010.521945 PMID: 21077004
12. Rennie MJ, Kelly SJ, Bush S, Spurrs RW, Austin DJ, Watsford ML. Phases of match-play in professional Australian Football: Distribution of physical and technical performance. J Sports Sci. 2020 Apr 28; 0(0):1–8. https://doi.org/10.1080/02640414.2020.1754726 PMID: 32342727
13. Corbett DM, Sweeting AJ, Robertson S. Weak Relationships between Stint Duration, Physical and Skilled Match Performance in Australian Football. Front Physiol [Internet]. 2017 [cited 2021 Feb 25]; 8. Available from: https://www.frontiersin.org/articles/10.3389/fphys.2017.00820/full?report=reader PMID: 29109688
14. Davids K, Button C, Bennett SJ. Dynamics of skill acquisition: a constraints-led approach [Internet]. Champaign, Illinois: Human Kinetics; 2008 [cited 2019 Jun 20]. http://www.humankinetics.com/products/showproduct.cfm?isbn=9780736036863
15. Newell KM. Constraints on the development of coordination. In: Wade M, Whiting H, editors. Motor Development in children: Aspects of coordination and control. Dordrecht, The Netherlands: Martinus Nijhoff; 1986. p. 341–60.
16. Balagué N, Pol R, Torrents C, Ric A, Hristovski R. On the Relatedness and Nestedness of Constraints. Sports Med—Open. 2019 Feb 11; 5(1):6. https://doi.org/10.1186/s40798-019-0178-z PMID: 30742241
17. Aminikhanghahi S, Cook DJ. A survey of methods for time series change point detection. Knowl Inf Syst. 2017 May 1; 51(2):339–67. https://doi.org/10.1007/s10115-016-0987-z PMID: 28603327
18. Corbett DM, Sweeting AJ, Robertson S. A change point approach to analysing the match activity profiles of team-sport athletes. J Sports Sci. 2019 Jul 18; 37(14):1600–8. https://doi.org/10.1080/02640414.2019.1577941 PMID: 30747582
19. Bardwell L, Fearnhead P, Eckley IA, Smith S, Spott M. Most Recent Changepoint Detection in Panel Data. Technometrics. 2019 Jan 2; 61(1):88–98.

20. Browne P, Sweeting AJ, Woods CT, Robertson S. Methodological Considerations for Furthering the Understanding of Constraints in Applied Sports. Sports Med—Open. 2021 Apr 1; 7(1):22. https://doi.org/10.1186/s40798-021-00313-x PMID: 33792790
21. Teune B, Woods C, Sweeting A, Inness M, Robertson S. The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. Eur J Sport Sci. 2021 Jul 26; 0(ja):1–20. https://doi.org/10.1080/17461391.2021.1958011 PMID: 34304723
22. R Core Team. R: A Language and Environment for Statistical Computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2019. https://www.R-project.org/
23. Landis JR, Koch GG. The Measurement of Observer Agreement for Categorical Data. Biometrics. 1977; 33(1):159–74. PMID: 843571
24. Zeileis A, Grothendieck G. zoo: S3 Infrastructure for Regular and Irregular Time Series. J Stat Softw. 2005 May 21; 14(1):1–27.
25. Killick R, Eckley IA. changepoint: An R Package for Changepoint Analysis. J Stat Softw. 2014 Jun 25; 58(1):1–19.
26. Bardwell L, Eckley I, Fearnhead P, Grose D. changepoint.mv: Changepoint Analysis for Multivariate Time Series [Internet]. 2020 [cited 2021 Jul 13]. https://CRAN.R-project.org/package=changepoint.mv
27. Fleay B, Joyce C, Banyard H, Woods C. Manipulating Field Dimensions During Small-sided Games Impacts the Technical and Physical Profiles of Australian Footballers. J Strength Cond Res. 2018 Jul 1; 32(7):2039–44. https://doi.org/10.1519/JSC.0000000000002423 PMID: 29337834
28. Nunes NA, Gonçalves B, Davids K, Esteves P, Travassos B. How manipulation of playing area dimensions in ball possession games constrains physical effort and technical actions in under-11, under-15 and under-23 soccer players. Res Sports Med. 2020 May 26; 0(0):1–15. https://doi.org/10.1080/15438627.2020.1770760 PMID: 32452730
29. Bonney N, Ball K, Berry J, Larkin P. Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. J Sports Sci. 2020 Jul 1; 30 (21):2430–6.
30. Davids K, Glazier P, Araújo D, Bartlett R. Movement systems as dynamical systems: the functional role of variability and its implications for sports medicine. Sports Med Auckl NZ. 2003; 33(4):245–60. https://doi.org/10.2165/00007256-200333040-00001 PMID: 12688825
31. Sullivan MO, Woods CT, Vaughan J, Davids K. Towards a contemporary player learning in development framework for sports practitioners. Int J Sports Sci Coach. 2021 Mar 22;17479541211002336.
32. Chow JY. Nonlinear Learning Underpinning Pedagogy: Evidence, Challenges, and Implications. Quest. 2013 Oct 1; 65(4):469–84.
33. Robertson PS. Man & machine: Adaptive tools for the contemporary performance analyst. J Sports Sci. 2020 Jun 12; 38(18):2118–26. https://doi.org/10.1080/02640414.2020.1774143 PMID: 32530736
34. Greenwood D, Davids K, Renshaw I. Experiential knowledge of expert coaches can help identify informational constraints on performance of dynamic interceptive actions. J Sports Sci. 2014 Feb 25; 32 (4):328–35. https://doi.org/10.1080/02640414.2013.824599 PMID: 24016400

VICTORIA UNIVERSITY

THE NEW WAY TO DO UNI

OFFICE FOR RESEARCH TRAINING, QUALITY AND INTEGRITY

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)

Title of Paper/Journal/Book: A method to inform team sport training activity duration with change point analysis

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0265848

Surname: Teune First name: Ben

Institute: Institute for Sustainable Industries and Liveabl Candidate's Contribution (%): 75

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 26/07/2021

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] 27/07/2022

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

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

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

3. There are no other authors of the publication according to these criteria;
4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and
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 storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Carl Woods	5	Assisted with theoretical positioning, feedback and revisions	[redacted]	18/07/22
Alice Sweeting	5	Assisted with methodology, feedback and revisions		19/07/22
Mathew Inness	5	Assisted with feedback and revisions		26/07/22
Sam Robertsons	10	Assisted with concept and study design, feedback and revisions		27/07/22

Updated: September 2019

A method to inform team sport training activity duration with change point analysis

6.1 Abstract

Duration is a key component in the design of training activities in sport which aim to enhance athlete skills and physical qualities. Training duration is often a balance between reaching skill development and physiological targets set by practitioners. This study aimed to exemplify change point time-series analyses to inform training activity duration in Australian Football. Five features of player behaviour were included in the analyses: disposal frequency, efficiency, pressure, possession time and player movement velocity. Results of the analyses identified moments of change which may be used to inform minimum or maximum activity durations, depending on a practitioner's objectives. In the first approach, a univariate analysis determined change points specific to each feature, allowing practitioners to evaluate activities according to a single metric. In contrast, a multivariate analysis considered interactions between features and identified a single change point, reflecting the moment of overall change during activities. Six iterations of a training activity were also evaluated resulting in common change point locations, between 196 and 252 seconds, which indicated alterations to player behaviour between this time period in the training activities conduction. Comparisons of feature segments before and after change points revealed the extent to which player behaviour changed and can guide such duration decisions. These methods can be used to evaluate athlete behaviour and inform training activity durations.

6.2 Introduction

Sport practitioners often use games-based training activities, or drills, to facilitate the development of physiological capacities and skill qualities of team sport athletes (Corbett et al., 2018; Gabbett et al., 2009)]. A key component of the design of such training activities relates to their duration, with practitioners needing to consider the appropriate time for skill learning to occur, while balancing physiological targets needed to improve performance and minimise injury risk (Vickery & Nichol, 2020). When evaluating training duration, contextualising player behaviour as a function of time provides more detailed insights into how and why certain outcomes have occurred (Glazier, 2017). For example, Australian football (AF) players reduce aggregate physical and technical performance following periods of peak physical intensity in match play (Black et al., 2016) or during the second half of match play (Black, Gabbett, Naughton, et al., 2019). In football, second half physical activity is influenced by first half activity levels (Sparks et al., 2016). Accordingly, such insights allow training to be designed more specifically to player activity levels. Suitable time sensitive data analyses may help inform training duration by providing measures of the fluctuation of player behaviour during training activities, which may indicate a decline in the efficacy of the aims of a particular activity. However, specific techniques to achieve this have not yet been applied to support training prescription.

To inform and evaluate training in team sports, data are typically collected from multiple sources, such as player tracking devices or manual annotation. Commonly, these data are reported using aggregate measures such as distance run, average speed or the volume of skill executions (Corbett et al., 2018; Gabbett et al., 2009). Such measures have also been compared with aggregate match data to determine the extent to which training activities reflect match demands (Browne et al., 2020; Corbett et al., 2018; Ireland et al., 2019). However, aggregate measures remain limited in utility as they do not represent the fluctuation of such measures as a function of time. In attempts to alleviate this, player speed has been analysed during matches as subsets of varying time periods such as rolling (between one and ten minutes) time windows (Clarke et al., 2021), five-minute blocks (Carling & Dupont, 2011), sub-phases of play (Rennie et al., 2020) or player on-field stints (Corbett et al., 2017).

Analyses of measures in a continuous format may yield further detailed insights. The use of continuous measurement is further supported by the framework of the constraints-led approach (Davids et al., 2008). This framework conceptualises constraints, such as pressure and time, as boundaries of the performer-environment system which shape the emergence of skilled behaviour. Specifically, constraints emerge and decay over varying time scales, and capturing this change over time is crucial in understanding and contextualising athlete behaviour (Balagué et al., 2019; Newell, 1986). Accordingly, a continuous time-series analysis, which evaluates changing contextual information and identifies when meaningful change has occurred, could be beneficial in informing training durations.

Change point detection, also known as time series segmentation, is an analytical method of determining specific locations in a time-series when a meaningful change has occurred. This algorithm can be used to detect single or multiple change points and has been widely applied in areas such as medical monitoring and climate change detection (Aminikhanghahi & Cook, 2017). In sport, change point detection has been applied in AF match play to segment player velocity data to identify potential interchange moments (Corbett et al., 2019). Recent advances to change point detection can also now perform multivariate analysis (Bardwell et al., 2019). In this approach, multiple sequences of data are combined to form a single time series with multiple observations, which allows for the detection of change points common across multiple time series (Bardwell et al., 2019). Multivariate change point detection may be beneficial in sport where multiple sources of data can be integrated to evaluate a single activity (Browne et al., 2021; Glazier, 2017). For example, athlete physical and skilled behaviour could be analysed together to detect moments of change within specific team-sport training activities. This may inform activity duration by objectively identifying when skilled and/or physical behaviour deviates meaningfully from specific training objectives. Thus, this study aimed to apply change point analysis as a method to inform team sport training activity duration, exemplified in AF.

6.3 Methodology

6.3.1 Participants

Participants were a convenience sample of listed players from a single professional AF club (n = 43; 84 ± 8.2 kg; 187 ± 8.1 cm; 24.5 ± 3.6 y). All players were injury free at the time of participation. Ethics approval was obtained from the Victoria University Human Research Ethics Committee (application number: HRE20-138). Written consent was provided by the club to use de-identified data collected as regular procedure during practice.

6.3.2 Data Collection

Data were collected during the 2021 Australian Football League pre-season. Through consultation with coaching staff and the literature (Corbett et al., 2018; Teune, Woods, et al., 2021b), five features of player behaviour were identified to evaluate a training activity (disposal frequency, efficiency, pressure, player possession time and player velocity). Skill event data and player tracking data were collected for each training activity repetition (n = 6) as it occurred during regular pre-season training sessions. The training activity was a small sided game with even teams, with each team being required to score at opposing ends of the ground. Each repetition ranged from ten to twelve players per team, depending on player availability, with a field area of approximately 90 x 60 m and a minimum duration of four minutes. For each activity repetition, team selection was quasi-randomised by coaching staff to standardise player positions and skill level. Typical AF rules were governed during the activities by a single coach.

To determine velocity during each training activity repetition, each participant wore a 10 Hz Global Positioning System device (Vector S7, Catapult, Catapult Sports Ltd, Melbourne) placed on their backs between their shoulder blades. Each participant wore the same device during all activities to reduce inter-unit error. Upon completion of the training sessions, tracking data was downloaded for each activity using the associated software package (Openfield, v3.3.0). The tracking data comprised a velocity measurement at each 10 Hz timestamp, for each player and activity, before being subsequently exported for analysis.

All data analysis was completed using the *R* programming language with the *RStudio* software (R Core Team, 2019) (version 1.3.1093). Velocity data was down sampled to a rate of 1 Hz, by calculating the mean velocity across every 10 fixed samples. This sample rate was used to simplify the merging process with skill event data. To determine the movement velocity during each activity repetition, the average velocity across all players was calculated at each 1 Hz time point.

To collect the skill event data, each training activity repetition was filmed with a two-dimensional camera (Canon XA25/Canon XA20) at 25 Hz from a side on or behind the goal perspective. After the training sessions, notational software (Hudl Sportscode, v12.2.44) was used to manually quantify the skill event data. A custom code window was used to record each kick or handball (a "disposal") according to its type (effective or ineffective) and two constraints on the disposal; possession time (<2 s or >2 s) and physical pressure (pressure or absent). Effectiveness was defined in accordance with Champion Data (Melbourne, Pty Ltd), where a handball or kick <40 m was deemed effective, if the intended target retained ball possession. A kick >40 m was deemed effective if kicked to a 50/50 contest or outnumber to the advantage of the attacking team. Possession time was defined as the time period between a player's ball possession gain and the moment of ball disposal. Pressure was defined as the physical presence of an opposition player within 3 m of the ball-carrier at the time of ball disposal. Two coders notated effectiveness and three coders notated the constraints (pressure and possession time). To assess the reliability of the notational coding, 168 disposals across three activities – observations not used in analysis – were selected for testing. The Kappa statistic (Landis & Koch, 1977) resulted in "almost perfect" inter-rater reliability for each variable (>0.8). Intra-rater reliability testing was completed after 14 days which resulted in Kappa statistics ranging from "substantial" (0.67- 0.8) to "almost perfect" across all coders (>0.8). All skill event data was then exported with a time-of-day timestamp rounded to the nearest second.

For each training activity repetition, the skill event data was joined with the velocity data according to the timestamp. The first and last disposal marked the beginning and end of each activity repetition and was used to determine a relative timestamp in the dataset where each repetition began at zero seconds. To determine disposal frequency as a time series, a rolling sum was applied using a 60 s window. This was achieved using the *rollsum* function from the *zoo* package (Zeileis & Grothendieck, 2005). A 60 s window was selected as practitioners commonly prescribe activity durations in whole minutes and this function would evaluate a metric analogous to those commonly reported (e.g. metres per minute) in physical training literature (Black et al., 2016; Black, Gabbett, Naughton, et al., 2019). To determine efficiency as a time series, the proportion of cumulative effective disposals to cumulative total disposals was represented as a moving percentage over time. To determine pressure as a time series, the proportion of cumulative pressured disposals to cumulative total disposals was represented as a moving percentage over time. To determine possession time as a time series, the proportion of cumulative disposals with <2 s possession time to cumulative total disposals was represented as a moving percentage over time. This process resulted in four sequences to describe the skilled behaviour during each training activity: disposal frequency (p/min), efficiency (%), pressured disposals (%) and disposals <2 s (%). As an example, efficiency is represented via binning (Fig 6.1a) and as a continuous series via the above methods (Fig 6.1b) to contrast the effect of the time series conversion.

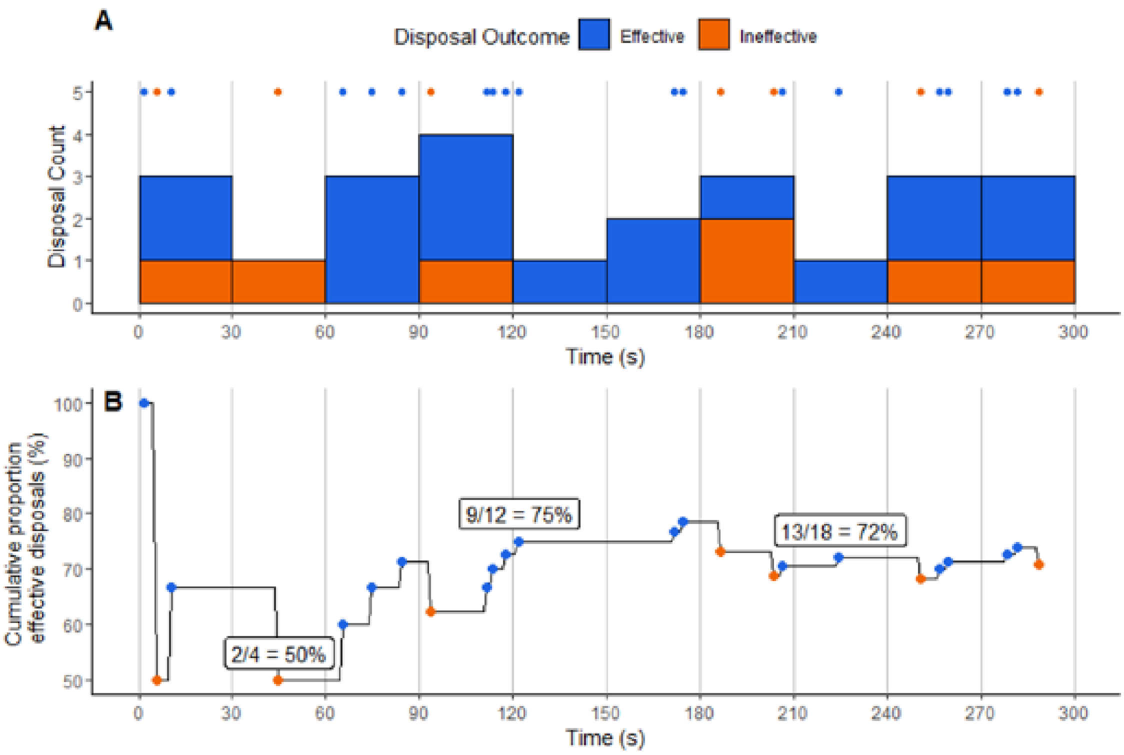


Figure 6.1 Example from a single activity repetition displaying disposal efficiency represented in 30 s bins (A) and continuously (B). Effective and ineffective disposal events are represented by the points. Three periodic annotations are provided to help describe the sequence calculation in panel B.

6.3.3 Statistical Analysis

To estimate the time point during the activities when properties of the time-series change for each feature, the *cpt_mean* function from the *changepoint* package was used (Killick & Eckley, 2014). This function identifies the time point in a sequence where an abrupt change in the sequence mean occurs. The method chosen was AMOC (at most one change) which specifies the algorithm to search for a maximum of one change point in the sequence. This was specified due to the short duration of activities and for feasibility reasons for the end user. The change point algorithm was applied to the sequences of each of the five features for each activity. Each sequence was subsequently segmented according to its change point location.

To determine a single time location common for all features during each activity repetition, a multivariate change point analysis was performed (Bardwell et al., 2019). To achieve this the *mrc* function from the *Changepoint.mv* package was used (Bardwell et al., 2020). This function determines common change point locations across multiple sequence inputs of the same length. The features of each training activity were normalised to allow comparison across different measures. The *mrc* function was applied across the normalised feature sequences for each activity. The function parameters were set where the cost was "mean", specifying the algorithm to search for a change in the sequence means, and the maximum number of change points to search for was set to one. This parameter was chosen to locate a single change point common across all five features of the activity. Each activity was then segmented according to the identified multivariate change point location.

6.4 Results

Descriptive statistics are presented as means and standard deviations. Across six repetitions of the training activity, the mean duration was 298 ± 17 seconds, disposal frequency was 5.7 ± 1.1 disposals/min, efficiency was 79.5 ± 9.1%, pressure was 40.6 ± 16.3%, possession time was 27.5 ± 19.6% and velocity was 127 ±.7.2 m•min^{-1}. The total number of skill involvements and activity duration included in the sample was 185 and 29.2 minutes, respectively.

To demonstrate the univariate and multivariate change point analysis approach, the results for a single activity repetition are reported in Fig 6.2 and 6.3, respectively. The left-hand column of panels visualises when the change points occurred and the right-hand column of panels visualises the feature distribution, before and after the change point, to describe the extent of change. The univariate change point analysis of disposal frequency, efficiency, pressure, possession time and velocity resulted in change point located at 85, 172, 124, 64 and 135 s respectively (Fig 6.2). For each feature the mean and standard deviation of the segments, before and after the changepoint, are reported in Fig 6.4. The multivariate changepoint approach resulted in a single changepoint for all skill features located at 204 seconds (Fig 6.3). For each feature the mean and standard deviation of the segments, before and after the changepoint, are reported in Fig 6.4.

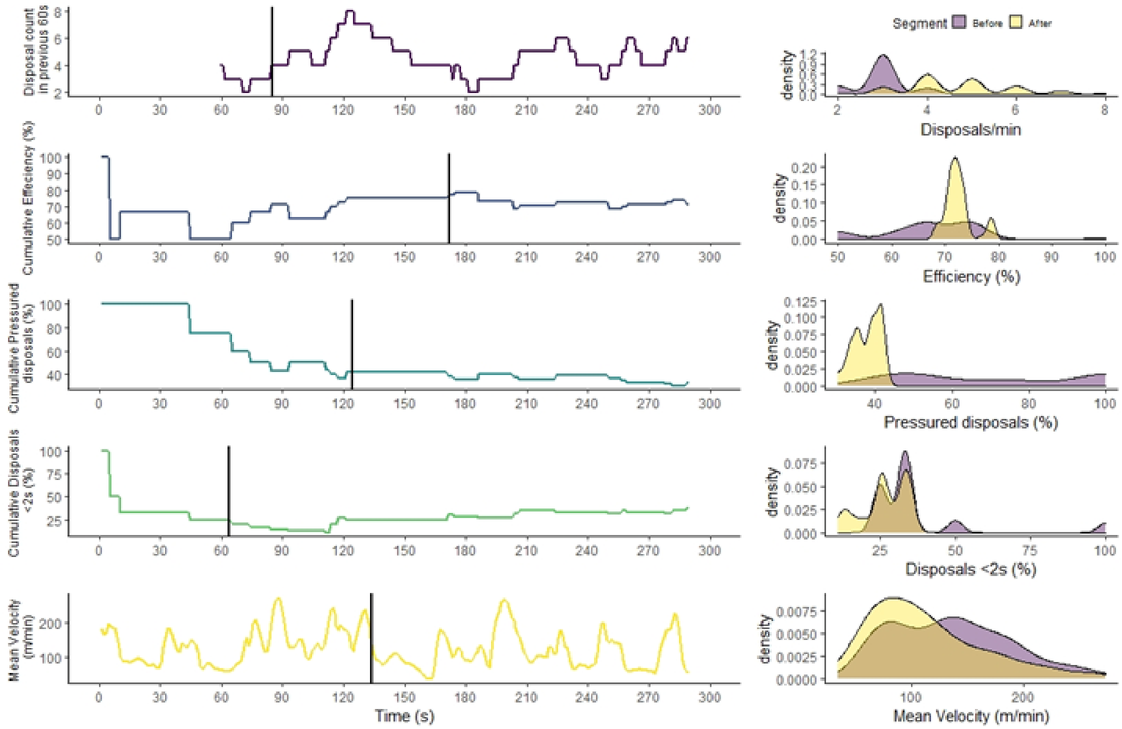


Figure 6.2 A univariate changepoint analysis of a single training activity. The left-hand column of panels displays the feature and the calculated changepoint location (black vertical line). The right-hand column of panels displays the distribution of the feature in each segment, before and after the changepoint.

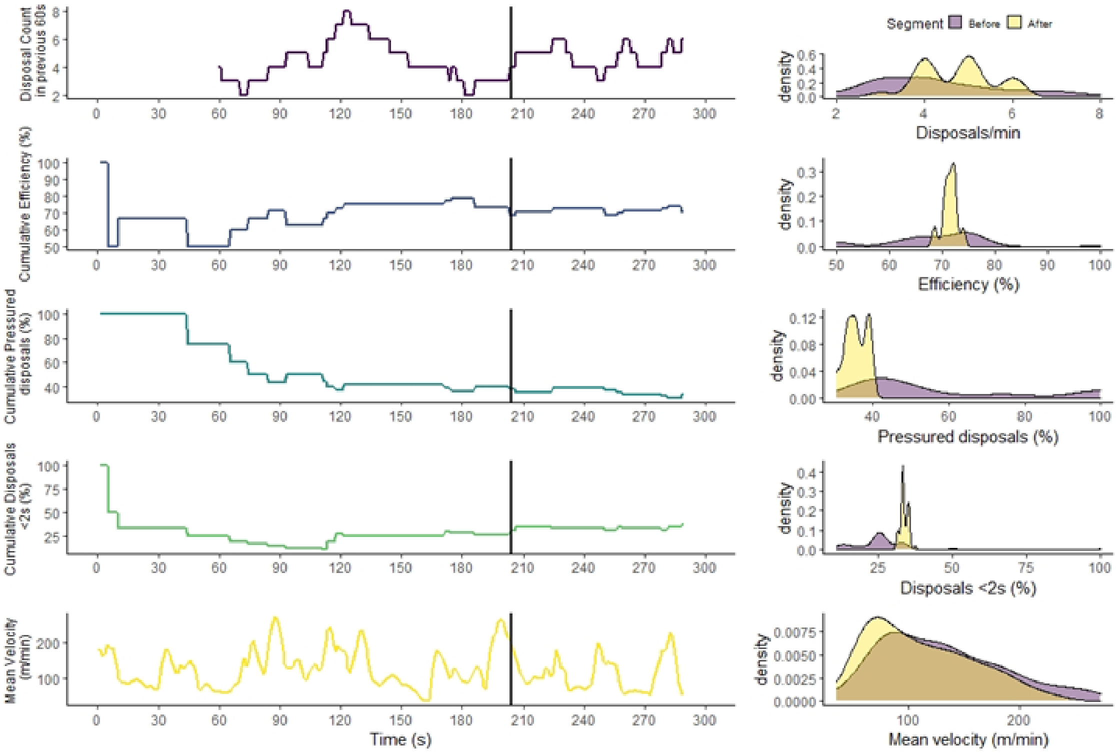


Figure 6.3 A multivariate changepoint analysis of a single training activity. The left-hand column of panels displays the feature and the calculated changepoint location (black vertical line). The right-hand column of panels displays the distribution of the feature in each segment, before and after the changepoint.

To inform activity duration, the results of the multivariate changepoint analysis on each activity repetition was visualised in Fig 6.5. Change point locations occurred at 196, 203, 205, 210, 219 and 252 s. Across six repetitions the mean location was 214.2 s with a standard deviation of 20.1 s.

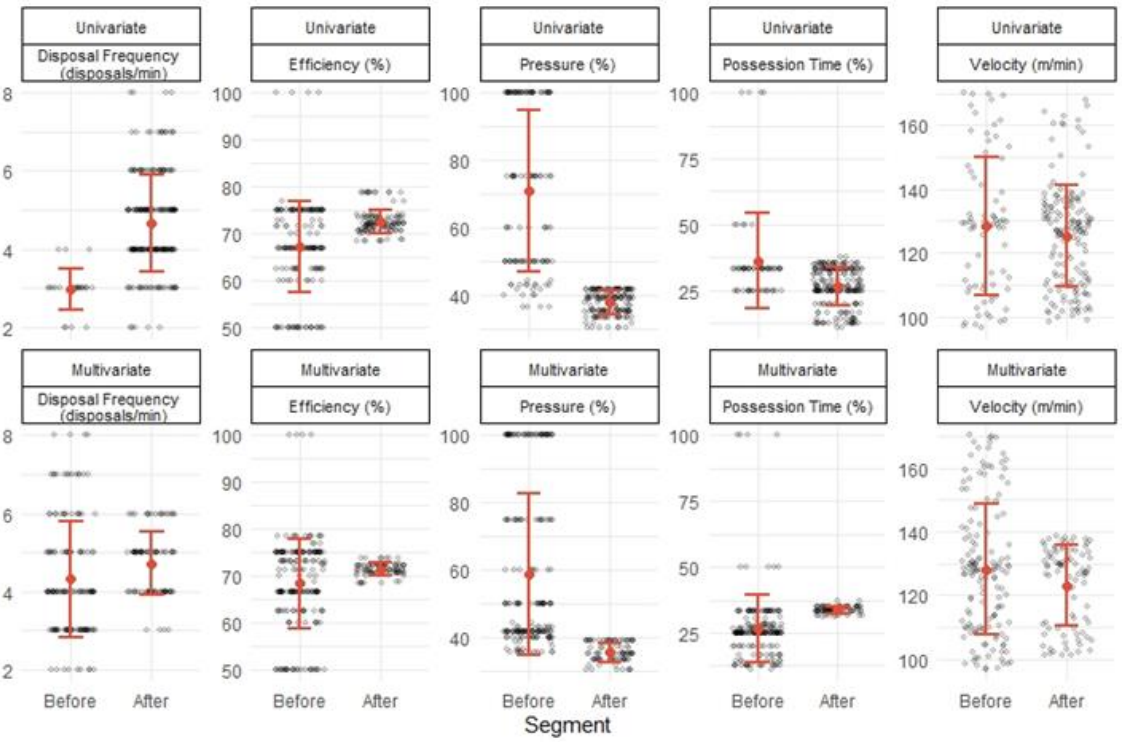


Figure 6.4 Summary statistics for segmented features according to a univariate and multivariate change point analysis of a single training activity. The orange point and error bars display the mean and one standard deviation of the segment, respectively. The black points each represent one second of the underlying segmented feature.

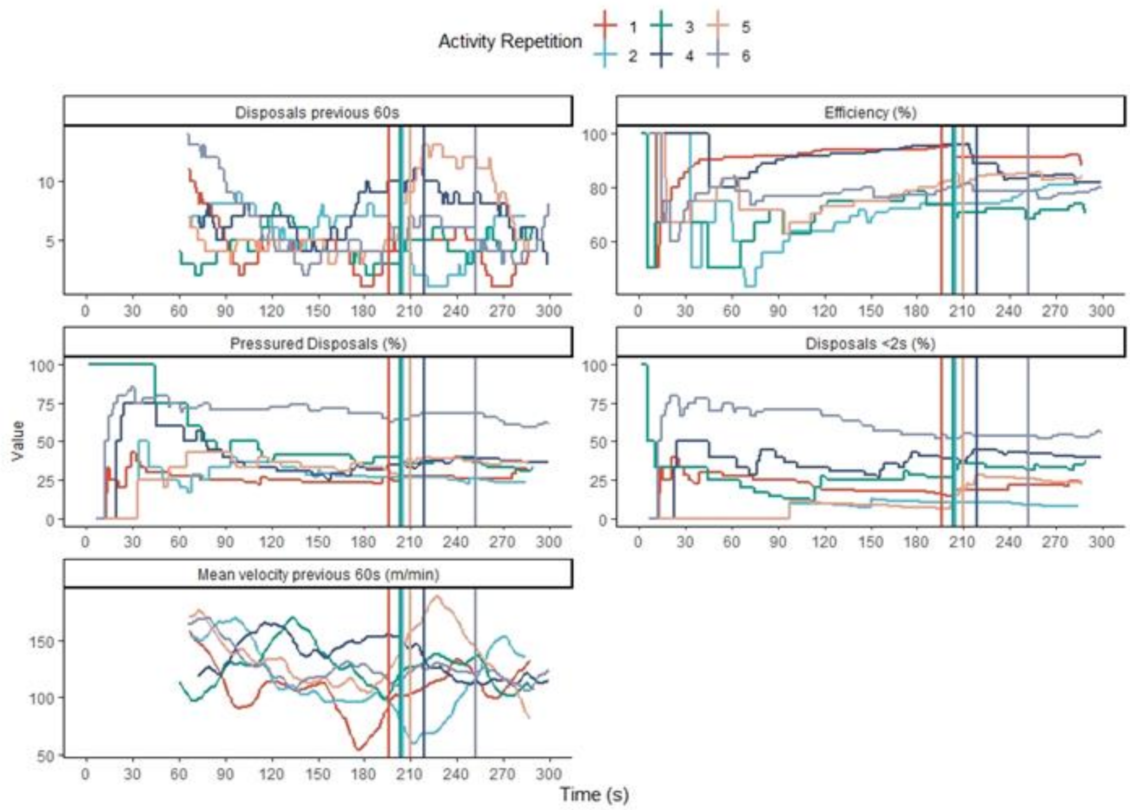


Figure 6.5 The sequences and multivariate changepoint locations for each feature of six activity repetitions. The feature value through the duration of the activity is displayed with straight vertical lines indicating a change point location. For velocity, the rolling mean over the previous 60 s is displayed to improve its visual interpretability. Feature sequences and changepoint locations are coloured according to activity repetition.

6.5 Discussion

This study presented a univariate and multivariate approach to determining change points during training activities that could be utilised by practitioners to inform training duration. Results demonstrated that the univariate approach was advantageous for providing information specific to each activity feature, which is useful for evaluating training according to a single metric. Comparatively, the multivariate approach is advantageous in analysing the interaction between multiple data sources, providing a simple output for the end user to inform a moment of overall change in the training activity. To guide informed activity duration decisions, visualisations were provided, summarising the univariate change point analysis of six repetitions of the training activity.

In the application of a univariate change point analysis, each of the five features were analysed separately. By resolving the change point location of each feature, a practitioner can identify when each feature meaningfully changed. To know the magnitude of change, the descriptive statistics comparing segments before and after the changepoint are shown in Fig 6.4. Fig 6.2 provides an example visualisation which may be useful for practitioners, displaying both when and to what extent each feature has changed during the activity.

According to key ideas of the constraints-led approach, player behaviour is continuously shaped under the interaction of various constraints (Davids et al., 2008). The change point analysis used here may, therefore, help practitioners identify periods of behavioural change in a continuous manner. For example, the change point for pressure was identified at 124 seconds, reducing the mean and standard deviation by 33.1% and 20.5%, relatively, after this point (Fig 6.4). A potential explanation for this observation is the effect of fatigue, which can impact a defending player's capacity to physically pressure the ball-carrier. Thus, it is possible that defenders may have adapted how they defended – deciding to cover or protect space, rather than chasing the ball-carrier. In this case, the change point could be used to identify how a new behavioural pattern has emerged, which can inform a practitioner's decisions regarding training design and duration in future iterations of the activity. Indeed, research has measured the aggregate influence of constraints, such as field area (Fleay et al., 2018), game type (Nunes et al., 2021) or playing number (Bonney et al., 2020) on physical and technical behaviour, however this relationship as a function of time presently remains unknown.

Determining a change point for each feature separately does have practical importance, allowing an activity to be evaluated according to a specific metric. For example, if a practitioner is seeking to ensure the efficiency of skills during a practice task does not drop below a certain level, a change point may be useful for noting when a meaningful shift has occurred, thereby allowing them to affect the design of the task. Further, univariate change point analysis has the potential to benefit practitioners with varying responsibilities, such as a conditioning coach and a skills coach. A conditioning coach, for example, can examine the change point for velocity to monitor the physiological demands on the players, while the skills coach can examine the change point for efficiency to monitor the difficulty of the task. This analysis provides a platform for collaboration between coaches to inform the duration of training that provides adequate time to achieve both physiological and skill targets. Importantly, although analysis has occurred separately, each of the features can still be visualised together (Fig 6.2), further encouraging collaboration between staff when evaluating the activity (Browne et al., 2021).

The multivariate change point approach analysed the interaction between features and identified one change point common across all features at 204 seconds (Fig 6.3). In the field, this approach provides a relatively simple output for practitioners, guiding decisions about practice design informed by a "general" or "overall" change point. As shown in Fig 6.4, the standard deviations of each feature after the change point were reduced. The larger variability of behaviour before the change point may, therefore, indicate exploratory actions of players searching for a stable solution suitable to the constraints of the task (Davids, Glazier, et al., 2003). Depending on the practitioner's objective for the activity, the identified change point may then serve as a potential "cut-off" point for facilitating exploratory player behaviour or a "minimum duration" required to provide adequate time for players to attune to their environment. Thus the change point can serve to analyse acute changes in the learning process to inform training design however, these should be considered within the longer time-scales of the learning process, such as weeks and months (M. O. Sullivan et al., 2021).

To further support a practitioner's decision making regarding practice design, six iterations of the same activity were analysed, in a multivariate manner, to evaluate trends in their change points. The visualisation in Fig 6.5 presents an exemplar technique to communicate information to practitioners on change point locations and feature values during each activity repetition. Five of the six change points appear similar across each repetition (Fig 6.5). From a practice design perspective, this gives practitioners confidence that during this period there is a change in overall player behaviour. This may serve as a more optimal activity duration to prescribe during future iterations of the activity, reducing time spent in undesired behavioural states. Importantly, variable behavioural states are likely to occur during match play and may reflect a training target for practitioners. The analysis may then aide to increase the efficiency of training sessions by saving valuable training time. In Fig 6.5, each activity repetition has been colour-coded so practitioners may identify specific results, such as an outlier, if desired. Retrospective inspection of video footage may provide additional information (e.g. weather or player injuries) which may assist in explaining the result.

An important practical aspect of change point analysis is that it accepts various metric representations, such as a rolling mean for disposal frequency and continuous velocity data from player tracking devices. This increases versatility in an environment, such as sport, where multiple data types are common. Specifying the algorithm to search for one change point provides a simple "before" and "after" summary of the data which improves the interpretability for practitioners. Moreover, as the advancement of technology continues in sport, the implementation of an on-line change point analysis could provide further benefits to practitioners, which could be applied to provide real-time feedback during an activity. This could identify the moment a behavioural change occurs to signal the end of an activity rather than relying on a predetermined time. Alternatively, the change point may present a critical moment for practitioner intervention during a practice task. For example, certain constraints could be manipulated to perturb or preserve the efficiency of disposals during a practice task, such as introducing number imbalances to make it easier or harder for a team's offence. This may be used to disrupt the players transition into a stable state, encouraging further exploration, or can nudge the players towards more optimal stable solutions (Chow, 2013). Irrespective, this analysis demonstrates how empirical and experiential knowledge of practitioners can be blended, exhibiting a balanced interaction between "man and machine" (Robertson, 2020), while still preserving the domain specific expertise of practitioners (Greenwood et al., 2014).

Due to the applied nature of this research, there are some limitations. Only four skill features and one physical feature were collected. To increase to the understanding of player behaviour over time, other features, like target pressure, kick distance, high-speed running or sprint frequency could be included. Additionally, parameters for the change point analysis were set to search for one change point. Thus, future work could investigate the impact of multiple change points in analysing behaviour fluctuations during training activities. While a 60 s window was applied to determine disposal frequency, future work could investigate the influence of other rolling windows on the stability of this metric. Further, future work could explore change point analysis between athletes to account for potential individual differences which may exist. This may support the design of player-specific training durations, information which would be of use to conditioning and medical staff when re-integrating players into team training following injury. Finally, increasing the number of activity iterations presented here from six may help alleviate potential confounding factors of results, such as fluctuating weather conditions or teams.

6.6 Conclusion

This study applied a univariate and multivariate change point analysis to inform training duration. The univariate approach provided change points for each feature, information that would be beneficial for practitioners seeking specific guidance on the evaluation of key metrics to inform the duration of training activities. The multivariate approach provided a single time point of general change and may be broadly indicative of players transitioning into different behavioural states. Evaluating multiple repetitions of the same activity is useful for finding trends in behavioural change and can identify critical points during an activity which can guide decisions around activity duration or even constraint manipulation. Given the practicality of the results presented here, practitioners are encouraged to adapt similar analyses to inform their own training designs.

CHAPTER SEVEN – STUDY V

Chapter Overview

Chapter Seven is the fifth of five studies contained in this thesis. This chapter expands on the previous studies within this thesis, which focus on skilled behaviour, by integrating aspects of physical and tactical performance. Furthermore, where Chapters Four and Five explored training evaluation across multiple activities, this chapter supports the analysis of specific behaviours within a single activity. Specifically, this study explores methods to evaluate the influence of a team number constraint manipulation on interactions between technical, tactical and physical player behaviour.

The content of this chapter is an accepted manuscript of an article published by PLoS Journals in PLoS ONE on 2n2 December 2022, available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0278644

PLOS ONE

RESEARCH ARTICLE

Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour

Ben Teune[1,2]*, **Carl Woods**[1☯], **Alice Sweeting**[1☯], **Mathew Inness**[1,2☯], **Sam Robertson**[1☯]

1 Institute for Health and Sport (iHeS), Victoria University, Melbourne, Australia, **2** Western Bulldogs, Melbourne, Australia

☯ These authors contributed equally to this work.
* benteune@outlook.com

Citation: Teune B, Woods C, Sweeting A, Inness M, Robertson S (2022) Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour. PLoS ONE 17(12): e0278644. https://doi.org/10.1371/journal.pone.0278644

Editor: Chris Connaboy, Rosalind Franklin University of Medicine and Science Doctor William M Scholl College of Podiatric Medicine, UNITED STATES

Received: July 6, 2022

Accepted: November 20, 2022

Published: December 1, 2022

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pone.0278644

Abstract

Evaluating practice design is an important component of supporting skill acquisition and improving team-sport performance. Constraint manipulations, including creating a numerical advantage or disadvantage during training, may be implemented by coaches to influence aspects of player or team behaviour. This study presents methods to evaluate the interaction between technical, tactical and physical behaviours of professional Australian Football players during numerical advantage and disadvantage conditions within a small-sided game. During each repetition of the game, team behaviour was manually annotated to determine: *repetition duration*, *disposal speed*, *total disposals*, *efficiency*, and *disposal type*. Global Positioning System devices were used to quantify tactical (*surface area*) and physical (*velocity* and *high intensity running*) variables. A rule association and classification tree analysis were undertaken. The top five rules for each constraint manipulation had confidence levels between 73.3% and 100%, which identified the most frequent behaviour interactions. Specifically, four advantage rules involved high surface area and medium high intensity running indicating the attacking team's frequent movement solution within this constraint. The classification tree included three behaviour metrics: surface area, velocity 1SD and repetition duration, and identified two unique movement solutions for each constraint manipulation. These results may inform if player behaviour is achieving the desired outcomes of a constraint manipulation, which could help practitioners determine the efficacy of a training task. Further, critical constraint values provided by the models may guide practitioners in their ongoing constraint manipulations to facilitate skill acquisition. Sport practitioners can adapt these methods to evaluate constraint manipulations and inform practice design.

Introduction

Sport coaches can design practice tasks to facilitate athlete development and support athlete learning and performance [1]. Coaches, along with other sport practitioners, should therefore consider the design of practice tasks which most effectively achieve their goals, whilst

Data Availability Statement: All relevant data are within the paper and its Supporting information files.

Funding: The author(s) received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist.

facilitating skill acquisition [2, 3]. A pedagogical approach, which may be used by practitioners to support the design of practice tasks, is constraint manipulation [2, 4]. Constraints represent boundaries or limitations to an athlete's interactions with their environment and the task being performed [5]. Constraint manipulations have been effective at guiding movement exploration and enhancing skill development in baseball batting [6] and swimming [7]. Specifically, in team sports, constraints such as field size or task rules, may be modified to guide the intentions, perceptions and actions of athletes while performing a practice task [8]. Athletes, therefore, must adapt their tactical (e.g. spatiotemporal movements), physical (e.g. distance and speed of locomotion), and/or technical (e.g. ball passing movements) behaviours to form movement solutions which aim to satisfy the constraints of a given task [9].

Evaluating the influence of a constraint manipulation on athlete behaviour is useful to understand the efficacy of what was manipulated and potentially support practitioners in (re) designing practice tasks [10]. The effect of constraint manipulations, including field size [11–13], the number of players [14–16] and task rules [15, 17, 18], on multiple facets of team and athlete behaviour, have been examined. To exemplify, field size manipulations can influence the lateral and longitudinal team width of players on the same and opposing teams [18, 19]. Field size is also positively related to the physical output of players, such as total distance covered [11]. Conversely, field size can be negatively related to the frequency of some technical actions, such as tackles or passes, in Australian football (AF) and field hockey [11, 13]. For example, if field size increased, the number of technical actions by athletes may decline due to the larger area available for athletes to move within. In contrast, when field size is decreased, the number of technical actions may be increased due to athletes needing to dispose the ball in a smaller area available. However, the interactions between a wider range of player behaviours, including technical, tactical and physical attributes, when manipulating constraints in AF training remains to be explored. Given the multi-faceted nature of sports performance, sports analysis should consider how such behaviours may interact and influence one another [20].

The constraints-led approach is a conceptual framework which advocates for the manipulation of practice task features (e.g. team size) to facilitate skill development [1, 4]. According to the constraints-led approach, constraints do not act in isolation but interact with one another, often in a non-linear manner [2]. Therefore, the manipulation of one constraint may have a dynamic influence on other constraints, with its influence changing or developing in different directions and over time. Thus, a challenge for practitioners is to understand how the manipulation of a single constraint can impact the many facets of an athletes performance [21]. Accordingly, it is pertinent to measure constraint interaction in order to provide appropriate contextual information when evaluating player behaviour [22, 23]. Importantly, determining constraint interactions highlights how the expression of a constraint changes when considered alongside other constraints. Further, from an applied perspective, the constraints-led approach has been suggested as an appropriate framework to support inter- and multi-disciplinarity in high performance support teams [20, 24]. For example, evaluating the skill and physical output of athletes together, associated with constraints manipulation in practice tasks, can foster interaction and collaboration between high performance and sports coaching staff [25, 26]. This may occur by providing a single report for multiple staff to cooperate in designing appropriate training environments to target complex goals in a single drill or training session. To this end, methods which can support practitioners to evaluate constraint interaction may enhance their training design.

Multivariate analytical techniques are advantageous for understanding constraint interaction [22, 24]. Such techniques, including rule association or classification and regression trees, have been applied to evaluate AF match kicking [22, 27], goal kicking [28] and skilled actions during training activities [10]. The advantages of these analyses have been discussed regarding the prevalence of constraints during AF goal kicking [28]. Specifically, their flexibility to suit various data types, while considering non-linear relationships, and their ease of interpretability are highlighted. The interpretability and flexibility of analytical outputs should be considered to suit the needs of coaches and facilitate practical implementation of findings. Accordingly, the application of these techniques to inform team sport training design may be beneficial. Methods which can inform training design may support practitioners' decision making by guiding their attention toward key constraint interactions [24, 29]. Thus, the current study aimed to demonstrate methods to evaluate the influence of a numerical constraint manipulation on the interaction between technical, tactical and physical player behaviour.

Methodology

Participants

Participants were a convenience sample of professional players from one AF club ($n = 41$, height = 187.7 ± 8 cm, mass = 84.4 ± 8.6 kg, age = 24.7 ± 3.8 years). All players were injury free at the time of participation. Ethics approval was obtained from the Victoria University Human Research Ethics Committee (application number: HRE20-138). Written consent was provided by the club to use de-identified data collected from the participants, as a regular procedure during practice.

Data collection

Data were collected for a single training task repeated ($n = 69$) throughout the 2022 Australian Football League pre-season training period (November 2021 –February 2022). Team selection was quasi-randomised by coaching staff on each occasion to balance team skill level. The training task comprised a small-sided game involving two teams of players competing against each other on a field approximately 80 m x 60 m (approximately 25% of a competition size AF field). The aim of the task was to move the ball from one end of the field to the other, while the defending team aimed to oppose this ball movement. The task ended when a shot on goal or a turnover was achieved. A team number constraint was manipulated by coaches, across all repetitions, whereby one team of seven competed against a team of eight, providing each team with either a numerical advantage (plus one) or disadvantage (minus one). For context, the practice task provided approximately 320 m^2/player while AF competition fields provide approximately 540 m^2/player. At the halfway point during each training session, the conditions were swapped so that both teams experienced each numerical constraint manipulation, in attack and defence. Task repetitions were defined by the sequences of play during the training activities, beginning with the ball at one end of the field until completion with the ball at the opposite end. Accordingly, repetitions were collected for both the numerical advantage ($n = 32$) and the disadvantage ($n = 37$) conditions.

To collect data pertaining to the technical skill of the players, the training activities were filmed from a side-on and behind-the-goals perspective with a two-dimensional camera (Canon XA25/Canon XA20). The two angles were subsequently aligned after the session for manual annotation. Skill data were collected via notational analysis software (Hudl Sportscode v12.4.2) using the aligned vision. Each pass (or "disposal") was manually coded according to the type (kick or handball) and effectiveness (effective or ineffective). A kick or handball < 40 m, in which the intended target retained possession of the ball, or a kick > 40 m to a 50/50 contest or advantage to the attacking team, was deemed effective, in accordance with Champion Data (Melbourne, Pty Ltd), the commercial statistics provider for the Australian Football League. A single coder notated this information. Thus, intra-rater reliability was examined via the kappa statistic [30], with a 14 day intra-reliability test resulting in "almost perfect"

Table 1. Player behaviour metrics and associated definitions. 1SD = one standard deviation.

Type	Metric	Definition
Technical	Efficiency (%)	Percentage of effective disposals to total disposals
	Percentage Kicks (%)	Percentage of kicks to total disposals
	Total disposals (#)	Total number of disposals performed
	Repetition duration (s)	Time from beginning to end of repetition
	Disposal speed (disp/min)	Total disposals divided by repetition duration in minutes
Tactical	Surface Area (m^2)	Average surface area of attacking team minus average surface area of defending team
	1SD Surface Area (m^2)	Standard deviation of surface area of attacking team minus standard deviation of surface area of defending team
Physical	Velocity (m/min)	Average velocity of attacking team minus average velocity of defending team
	1SD Velocity (m/min)	Standard deviation of velocity of attacking team minus standard deviation of velocity of defending team
	HIR (m/min)	Average HIR metres per minute of attacking team minus average HIR metres per minute of defending team
	1SD HIR (m/min)	Standard deviation of HIR of attacking team minus standard deviation of HIR of defending team

https://doi.org/10.1371/journal.pone.0278644.t001

agreement (0.95). Using this information, the efficiency, percentage of kicks, disposal count and disposal speed were calculated for each repetition (Table 1).

To determine tactical and physical movement of players during the training tasks, spatio-temporal positioning and velocity of each participant was collected using 10 Hz Global Positioning System devices (Vector S7, Catapult, Catapult Sports Ltd, Melbourne) which were placed on the participant's back, between their shoulder blades. Each participant wore the same device between sessions and during all activities to reduce inter-unit error. After session completion, tracking data for each participant was downloaded using the associated software (Openfield v 3.3.1) and exported for analysis. This data comprised latitude, longitude and velocity values at each 10 Hz timestamp for each participant. Each participant's tracking data was then down sampled to a rate of 1 Hz by taking the mean latitude, longitude, and velocity across every ten fixed samples. This was done to simplify the subsequent merging process with skill event data. This, and all subsequent data analysis, was completed using the *R* programming language [31] with the *RStudio* software (v2021.09.2).

Participant spatiotemporal data then was used to determine the surface area of each team during each task repetition. All latitude and longitude data were first converted to x and y coordinates, in metres, relative to the minimum x and y values in the dataset. Surface area was then calculated by determining the area (m^2) between the outermost players, at each 1 Hz time point, through the application of a convex hull [32]. For each repetition, the mean and one standard deviation (1SD) of the surface area was determined for the attacking and defending team. 1SD is a measure of the variation or dispersion of sample values relative to the mean. The mean and 1SD were then converted to a differential between the attacking and defending team. These calculations were performed to provide values which describe the attacking team's tactical movement relative to the defensive team.

The tracking data was also used to determine the velocity and high intensity running (HIR) metres of each team during each repetition. HIR was defined as any running speed > 250 $m{\bullet}min^{-1}$ (or >15 km/h). The mean velocity was calculated for each player during each repetition and represented as $m{\bullet}min^{-1}$. These values were then used to determine the mean and 1SD in velocity for the attacking and defending team during each repetition. Similarly, HIR was calculated for each repetition and mean HIR was calculated for each player during each repetition and represented as m•min^{-1}. These values were then used to determine the mean and 1SD in HIR for each team during each repetition. Mean velocity, velocity 1SD, mean HIR, and HIR 1SD were represented as a differential between the attacking and defending team to provide values for the attacking team's physical movement relative to the defence.

Statistical analysis

A correlogram was used to explore any univariate linear relationships between the behaviour metrics, as listed in Table 1. To determine the influence of the team number constraint manipulation on player behaviours, two multivariate analytical approaches were applied: rule association and classification trees. To apply rule association, each behaviour metric was first discretised into three arbitrary categories: low, medium and high. These categories were chosen to align with the preferred output style of the end-users (i.e., coaches of the football club). This was achieved using the *discretizeDF* function in the *arules* package [33], using a cluster method set for three groups. Rules for each numerical condition were then generated using the *apriori* function, which uses the *Apriori* algorithm [34]. The *Apriori* algorithm identifies relationships between variables by producing rule sets, similar to if-then statements. For example, the rule {Efficiency = x, Surface Area = y} = > {Velocity = z} indicates if antecedent values of Efficiency and Surface Area occurred, then the consequent value of Velocity occurred. Rules may be evaluated via support (%), the frequency of a rule within a dataset, and confidence (%), the frequency of the consequent given the antecedents of the rule. Parameters of the *apriori* function were set to search for rules with a minimum support of 0.15, minimum confidence of 0.7, and a minimum rule length of four.

The second approach applied a classification tree using the *rpart* package [35]. The *rpart* function was used to classify the constraint condition of each task repetition based on the values of the behaviour metrics. The *rpart* function achieves this by partitioning the data according to specific values of variables which are most strongly linked to the outcome variable. The default parameters for the function were used with a complexity parameter of 0.01, a minimum split attempt of 29% (20 observations) and minimum terminal node observations set at seven (minimum split / 3).

Results

For the 32 numerical advantage repetitions, the mean duration was 16.3 s ± 8.2 s and the mean disposal count was 2.9 ± 1.3. For the 37 numerical disadvantage repetitions, the mean duration was 22.7 s ± 12.8 s and the mean disposal count was 3.6 ± 1.6. The distribution of each metric, within each condition is displayed in Fig 1. The correlogram was presented in Fig 2. Univariate correlations between all behaviour metrics were within 0.5 and -0.5 with the exception of positive correlations between total disposals and repetition duration (0.84) and between velocity and HIR (0.8).

For the rule association approach, the resulting cut-off values used during discretisation are displayed in Table 2 and the counts within each category of the discretisation are displayed in Fig 3. From the results of the *Apriori* algorithm, nine rules were generated for the numerical advantage condition and six rules were generated for the numerical disadvantage condition. The top five rules, by confidence, for each condition are displayed in Figs 4 and 5. For the numerical advantage condition, confidence ranged from 80% to 100% and for the numerical disadvantage condition, confidence ranged from 73.3% to 85.7%.

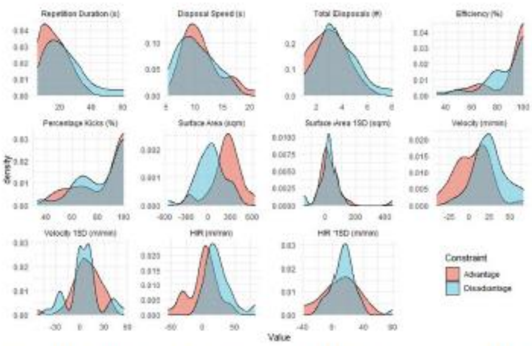


Fig 1. Distribution of each behaviour metric within advantage (red) and disadvantage (blue) constraint conditions.

https://doi.org/10.1371/journal.pone.0278644.g001

The resulting https://doi.org/10.1371/journal.pone.0278644.g001. The only variables used by the model to partition the data were surface area, repetition duration and velocity 1SD. Four terminal nodes are shown, two for each numerical condition with classification accuracies ranging from 71% to 94%. A visualisation of all behaviour metrics within each terminal node, scaled to allow comparison, was also provided (Fig 7).

Discussion

The aim of this study was to demonstrate methods to evaluate a numerical constraint manipulation while considering the interaction of player technical, tactical and physical behaviour. A rule association and classification tree approach were used to analyse player behaviour, under

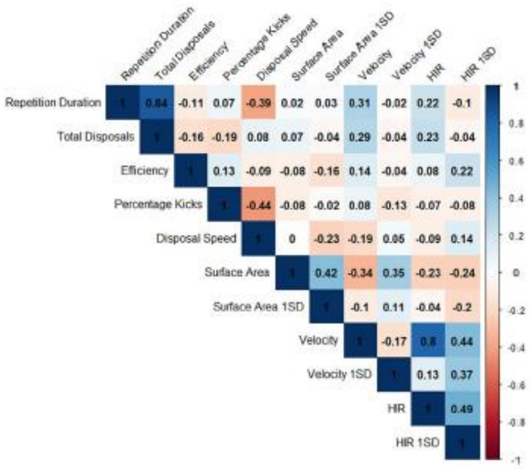


Fig 2. Correlogram of each behaviour metric. Each tile is labelled with the correlation coefficients between each metric and coloured according to this value as per the colour scale on the right (blue hues indicate a positive correlation and red hues indicate negative correlation).

https://doi.org/10.1371/journal.pone.0278644.g002

Table 2. Cut-off values used to discretise each behaviour metric.

Metric	Low	Med	High
Repetition Duration (s)	< 18.3	18.3 to 38.2	> 38.2
Total Disposals (#)	< 2.29	2.29 to 3.89	> 3.89
Disposal Speed (disp/min)	< 10	10 to 14.2	> 14.2
Efficiency (%)	< 61.3	61.3 to 88	> 88
Percentage Kicks (%)	< 69.3	69.3 to 88.8	> 88.8
Surface Area (m^2)	< -28.3	-28.3 to 237	> 237
Surface Area 1SD (m^2)	< 11.7	11.7 to 250	> 250
Velocity (m/min)	< 3.61	3.61 to 36.7	> 36.7
Velocity 1SD (m/min)	< -8.95	-8.95 to 21.5	> 21.5
HIR (m/min)	< -11.7	-11.7 to 27.1	> 27.1
HIR 1SD (m/min)	< 0.46	0.46 to 27.2	> 27.2

https://doi.org/10.1371/journal.pone.0278644.t002

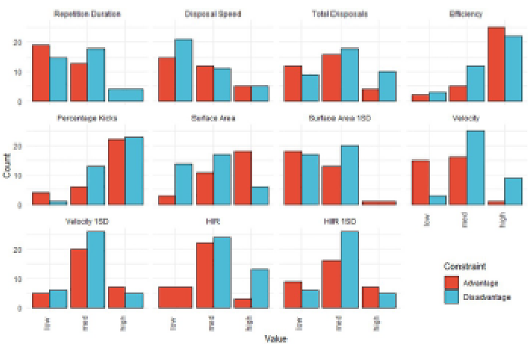


Fig 3. Results of the discretisation of each behaviour metric. Repetition counts for each category are displayed for the advantage (red) and disadvantage (blue) constraint conditions.

https://doi.org/10.1371/journal.pone.0278644.g003

the premise of supporting the design of practice tasks in team sport. The rule association provided a simple visualisation whereby coaches can identify associations between aspects of player behaviour. Additionally, the classification tree could be used to determine specific values of interest which can guide ongoing constraint manipulations in practice task designs.

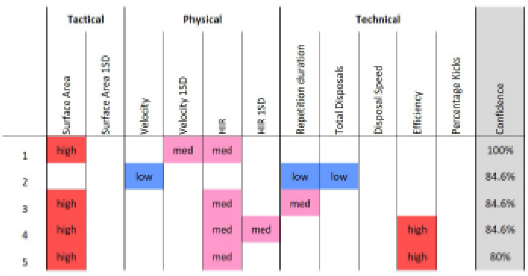
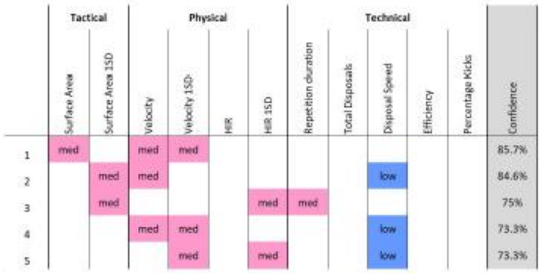


Fig 4. The top five rules generated for the advantage constraint condition, ordered by confidence. Each discretised metric is colour coded according to its category (red = high, pink = med, blue = low) for visual interpretability.

https://doi.org/10.1371/journal.pone.0278644.g004



	Tactical		Physical					Technical				
	Surface Area	Surface Area 1SD	Velocity	Velocity 1SD-	HIR	HIR 1SD	Repetition duration	Total Disposals	Disposal Speed	Efficiency	Percentage Kicks	Confidence
1	med		med	med								85.7%
2		med	med						low			84.6%
3		med				med	med					75%
4			med	med					low			73.3%
5				med		med			low			73.3%

Fig 5. The top five rules generated for the disadvantage constraint condition, ordered by confidence. Each discretised metric is colour coded according to its category (red = high, pink = med, blue = low) for visual interpretability.

https://doi.org/10.1371/journal.pone.0278644.g005

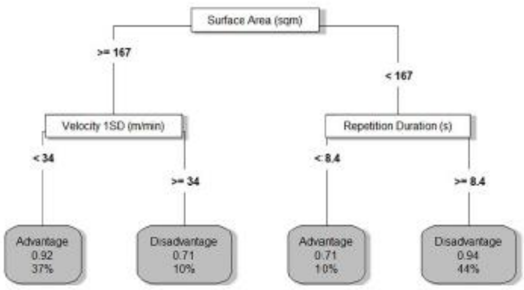


Fig 6. The classification tree used to model the constraint condition (advantage or disadvantage). Terminal nodes are labelled with the predicted constraint condition while the decimals indicate the accuracy of the fitted value and the percentages indicate the frequency of observations.

https://doi.org/10.1371/journal.pone.0278644.g006

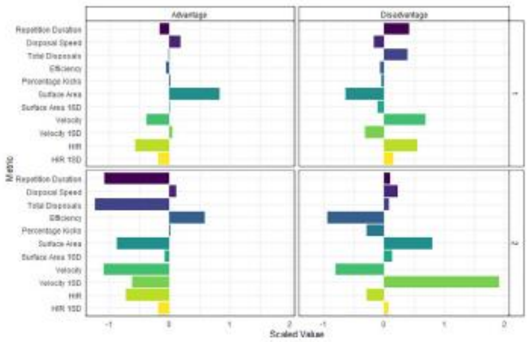


Fig 7. The average of each behaviour metric within the identified task solutions (1 and 2) for each constraint condition (advantage and disadvantage). The bar plot values are scaled to a mean of zero and a standard deviation of one to allow comparability between metrics.

https://doi.org/10.1371/journal.pone.0278644.g007

The results of the rule association analysis provide a simple heuristic which could support coach decision-making. The rules displayed in Figs 4 and 5 highlight which simultaneous behaviours players are exploiting to achieve the given task. This builds upon previous AF work using rule association to evaluate training [10] and match play [22, 27] through the inclusion of tactical and physical behavioural metrics. Moreover, the rule association identified non-linear relationships between behaviour metrics which were not determined in the linear exploration shown in Fig 2. Discretising continuous variables is a necessary step to perform rule association and presents both advantages and disadvantages for interpretation. Binning values into three categories; low, medium and high, may suit the communication preferences of coaches although, other quantities of bins may also be used. Decisions on bin quantities should be aimed at improving the coaches' ease of use and increasing the speed of their decision making, which therefore may vary. However, discretisation can reduce the explanatory power of continuous variables. For example, a range of values can be identified within each category but no specific values for player behaviour can be provided to the practitioner, limiting their utility for intervention.

The results of the rule association suggest that, when playing with a numerical advantage, teams used their additional player to spread over larger areas than their opposition. This was indicated as four of the five top rules for the advantage condition included high levels of surface area. Additionally, within each of these four rules, high surface area was associated with medium levels of HIR. This suggests that this level of physical running speed was required to achieve the levels of high surface area. Other metrics, including kick percentage and disposal speed, were not included in any of the top five rules. This indicated that the numerical advantage did not influence these behaviours, nor did they interact with others at a meaningful level. Contrastingly, in the numerical disadvantage condition, three of the top five rules involved low disposal speed. A team at disadvantage frequently exhibited a slower speed of play. Low disposal speed was also associated with medium surface area 1SD, medium velocity and medium velocity 1SD. Similar findings in investigations of other constraint manipulations, such as field density or team size, have reported simultaneous changes to skilled, physical and tactical behaviour of players in field hockey and soccer [13, 36] however, their interactions were not determined. In the current study, results of the rule association showed how interactions between the behaviours of players can be measured. Accordingly, these interactions are pertinent information for both a conditioning and skills coach. For example, a conditioning coach can monitor and prepare players for the specific work rates required to perform tactical manoeuvres influenced by the numerical constraint manipulation. This outcome highlights how the analysis can provide a platform for a multidisciplinary approach to support athlete development [24, 37].

The second rule for the numerical advantage condition presented three unique variables which were absent in any other rules. These variables were low repetition duration, low total disposals and low velocity. This indicates an alternate task solution was used by the players. In this solution, the ball is moved quickly down the field with a low quantity of disposals and lower running speed than the defence. This observation is similar to other work in AF, in which the inclusion of an additional attacker reduced the average velocity of the group [14]. This solution may emerge given a sudden exploitation of an opportunity, such as a lapse in defensive structure. Depending on the training objectives of coaches, training design may be modified to encourage or discourage performance of this solution. For example, to discourage this solution and further guide player's attention toward using their numerical advantage to maximise surface area, an additional task constraint of a minimum pass count could be implemented during the advantage condition.

Contrasted with rule association, the classification tree could be advantageous by enabling the data to be modelled in its continuous format. Accordingly, when using numerical data, critical values can be directly provided by the model which are influential on player behaviour. To exemplify, along the right branch of the tree (Fig 6), a common task solution for the numerically disadvantaged team was to slow the sequence of play down as indicated by the repetition duration of >8.4 s. This behaviour may have emerged as players sought additional time to create space against a team possessing an extra number, thereby maintaining possession of the ball. The repetition duration value of 8.4 s may be leveraged by a coach seeking to encourage greater exploration in task solutions. For example, a temporal constraint of 8 s may be introduced to challenge the stability of this solution for the team with the numerical inferiority. This may lead to the emergence of a new behavioural pattern, as players search to exploit both the numerical inequality and temporal constraint. Only three behaviours were found to be influenced by manipulation of the numerical constraint: surface area, velocity 1SD and repetition duration. This suggested that all other behaviours remained predominantly stable despite the numerical constraint manipulation. Using this information, coaches may choose to manipulate additional constraints, such as field dimensions or task rules, to perturb player behaviours and encourage variability [38].

The partitions provided by the classification tree may be used to identify the different task solutions performed by teams within each numerical constraint. A similar approach has been reported in swimming where a clustering analysis identified if learners were exploiting or exploring task solutions during training [7]. In the current study, the classification tree produced two terminal nodes for each numerical condition, suggesting two unique task solutions were exhibited within each constraint. The first solution was the most frequently used (advantage = 37%, disadvantage = 44%) and the second solution was the least frequently used (advantage = 10%, disadvantage = 10%). Fig 7 can thus highlight how technical, tactical and physical behaviours are organised simultaneously by teams to achieve the task goal. This may be advantageous as a complementary visualisation to the classification tree, reporting all behaviour metrics in addition to the three included in the classification tree. Through evaluations of these behaviours, coaches may seek to guide or nudge players towards new or more optimal task solutions, according to their training objectives [3].

Given the applied nature of the current study, some limitations exist which should be considered. Field sizes were approximately measured during data collection and some small variations may exist between training sessions. This, however, was controlled as closely as practically possible. Additionally, while players on each team were selected to balance skill level, player selection was inconsistent across each session. Accordingly, these factors may have influenced team behaviours between task repetitions. Some instances occurred where there was an unused player on the sideline (due to irregular numerical grouping) and players were permitted to substitute between repetitions. A total of 16 substitutions occurred during data collection which may have influenced the physical output of players. Although the validity and reliability of 10 Hz Global Positioning Systems have been assessed [39, 40], mean error of 96cm has been shown in such units [41]. It is unlikely this margin of error will have influenced results, given the large field sizes used, however this is yet to be determined. From an analytical perspective, only one measure of tactical behaviour was used during this study and future work may be directed to include other measures of collective team behaviour, such as centroid location, difference between team centroids, or team separateness. Finally, future work may seek to measure constraints on disposals, such as pressure or possession time, to provide further context to the technical actions performed during repetitions. The results, nonetheless, provide an enticing methodological platform for future work.

Conclusion

This study applied two multivariate analytical techniques, rule association and a classification tree, to evaluate the influence of a numerical advantage or disadvantage on the technical, tactical and physical behaviour of AF players during a small-sided training task. The rule association approach presented a simple and interpretable output for coaches which informed interactions between key behaviours during each constraint condition. The classification tree provided specific values of interest which may be used to inform further constraint manipulations to enhance practice task design. A visualisation of the different task solutions identified through the classification tree was provided to assist coaches in evaluating how players organise their movements within each constraint. These methods and visualisations are provided as tools which sport practitioners are encouraged to adopt to inform the design of their own training activities.

Supporting information

S1 Data. Advantage and disadvantage task repetitions.
(CSV)

Author Contributions

Conceptualization: Ben Teune, Sam Robertson.

Data curation: Ben Teune.

Formal analysis: Ben Teune.

Methodology: Ben Teune, Carl Woods, Sam Robertson.

Supervision: Carl Woods, Alice Sweeting, Mathew Inness, Sam Robertson.

Visualization: Ben Teune.

Writing – original draft: Ben Teune.

Writing – review & editing: Carl Woods, Alice Sweeting, Mathew Inness, Sam Robertson.

References

1. Davids K, Button C, Bennett SJ. Dynamics of skill acquisition: a constraints-led approach. Champaign, Illinois: Human Kinetics; 2008. http://www.humankinetics.com/products/showproduct.cfm?isbn=9780736036863
2. Chow JY. Nonlinear Learning Underpinning Pedagogy: Evidence, Challenges, and Implications. Quest. 2013; 65: 469–484. https://doi.org/10.1080/00336297.2013.807746
3. Woods CT, McKeown I, Rothwell M, Araújo D, Robertson S, Davids K. Sport Practitioners as Sport Ecology Designers: How Ecological Dynamics Has Progressively Changed Perceptions of Skill "Acquisition" in the Sporting Habitat. Front Psychol. 2020; 11: 654. https://doi.org/10.3389/fpsyg.2020.00654 PMID: 32390904
4. Renshaw I, Chow J-Y. A constraint-led approach to sport and physical education pedagogy. Phys Educ Sport Pedagogy. 2019; 24: 103–116. https://doi.org/10.1080/17408989.2018.1552676
5. Newell KM. Constraints on the development of coordination. In: Wade M, Whiting H, editors. Motor Development in children: Aspects of coordination and control. Dordrecht, The Netherlands: Martinus Nijhoff; 1986. pp. 341–360.
6. Gray R. Comparing the constraints led approach, differential learning and prescriptive instruction for training opposite-field hitting in baseball. Psychol Sport Exerc. 2020; 51: 101797. https://doi.org/10.1016/j.psychsport.2020.101797
7. Komar J, Potdevin F, Chollet D, Seifert L. Between exploitation and exploration of motor behaviours: unpacking the constraints-led approach to foster nonlinear learning in physical education. Phys Educ Sport Pedagogy. 2019; 24: 133–145. https://doi.org/10.1080/17408989.2018.1557133
8. Seifert L, Araújo D, Komar J, Davids K. Understanding constraints on sport performance from the complexity sciences paradigm: An ecological dynamics framework. Hum Mov Sci. 2017; 56: 178–180. https://doi.org/10.1016/j.humov.2017.05.001 PMID: 28499742

9. Torrents C, Ric A, Hristovski R, Torres-Ronda L, Vicente E, Sampaio J. Emergence of Exploratory, Technical and Tactical Behavior in Small-Sided Soccer Games when Manipulating the Number of Teammates and Opponents. PLOS ONE. 2016; 11: e0168866. https://doi.org/10.1371/journal.pone.0168866 PMID: 28005978

10. Teune B, Woods C, Sweeting A, Inness M, Robertson S. The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. Eur J Sport Sci. 2021; 22. https://doi.org/10.1080/17461391.2021.1958011 PMID: 34304723

11. Fleay B, Joyce C, Banyard H, Woods C. Manipulating Field Dimensions During Small-sided Games Impacts the Technical and Physical Profiles of Australian Footballers. J Strength Cond Res. 2018; 32: 2039–2044. https://doi.org/10.1519/JSC.0000000000002423 PMID: 29337834

12. Nunes NA, Gonçalves B, Davids K, Esteves P, Travassos B. How manipulation of playing area dimensions in ball possession games constrains physical effort and technical actions in under-11, under-15 and under-23 soccer players. Res Sports Med. 2021; 29: 170–184. https://doi.org/10.1080/15438627.2020.1770760 PMID: 32452730

13. Timmerman EA, Farrow D, Savelsbergh GJ. The effect of manipulating task constraints on game performance in youth field hockey. Int J Sports Sci Coach. 2017; 12: 588–594. https://doi.org/10.1177/1747954117727659

14. Bonney N, Ball K, Berry J, Larkin P. Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. J Sports Sci. 2020; 30: 2430–2436.

15. Timmerman EA, Savelsbergh GJP, Farrow D. Creating Appropriate Training Environments to Improve Technical, Decision-Making, and Physical Skills in Field Hockey. Res Q Exerc Sport. 2019; 90: 180–189. https://doi.org/10.1080/02701367.2019.1571678 PMID: 30794115

16. Vilar L, Esteves PT, Travassos B, Passos P, Lago-Peñas C, Davids K. Varying Numbers of Players in Small-Sided Soccer Games Modifies Action Opportunities during Training. Int J Sports Sci Coach. 2014; 9: 1007–1018. https://doi.org/10.1260/1747-9541.9.5.1007

17. Correia V, Araújo D, Duarte R, Travassos B, Passos P, Davids K. Changes in practice task constraints shape decision-making behaviours of team games players. J Sci Med Sport. 2012; 15: 244–249. https://doi.org/10.1016/j.jsams.2011.10.004 PMID: 22153899

18. Travassos B, Gonçalves B, Marcelino R, Monteiro R, Sampaio J. How perceiving additional targets modifies teams' tactical behavior during football small-sided games. Hum Mov Sci. 2014; 38: 241–250. https://doi.org/10.1016/j.humov.2014.10.005 PMID: 25457422

19. Frencken W, Van Der Plaats J, Visscher C, Lemmink K. Size matters: Pitch dimensions constrain interactive team behaviour in soccer. J Syst Sci Complex. 2013; 26: 85–93. https://doi.org/10.1007/s11424-013-2284-1

20. Glazier PS. Towards a Grand Unified Theory of sports performance. Hum Mov Sci. 2017; 56: 139–156. https://doi.org/10.1016/j.humov.2015.08.001 PMID: 26725372

21. Balagué N, Pol R, Torrents C, Ric A, Hristovski R. On the Relatedness and Nestedness of Constraints. Sports Med—Open. 2019; 5: 6. https://doi.org/10.1186/s40798-019-0178-z PMID: 30742241

22. Browne P, Sweeting AJ, Davids K, Robertson S. Prevalence of interactions and influence of performance constraints on kick outcomes across Australian Football tiers: Implications for representative practice designs. Hum Mov Sci. 2019; 66: 621–630. https://doi.org/10.1016/j.humov.2019.06.013 PMID: 31326736

23. Browne P, Woods CT, Sweeting AJ, Robertson S. Applications of a working framework for the measurement of representative learning design in Australian football. PLOS ONE. 2020; 15: e0242336. https://doi.org/10.1371/journal.pone.0242336 PMID: 33253204

24. Browne P, Sweeting AJ, Woods CT, Robertson S. Methodological Considerations for Furthering the Understanding of Constraints in Applied Sports. Sports Med—Open. 2021; 7: 22. https://doi.org/10.1186/s40798-021-00313-x PMID: 33792790

25. Corbett DM, Bartlett JD, O'connor F, Back N, Torres-Ronda L, Robertson S. Development of physical and skill training drill prescription systems for elite Australian Rules football. Sci Med Footb. 2018; 2: 51–57. https://doi.org/10.1080/24733938.2017.1381344

26. Teune B, Woods C, Sweeting A, Inness M, Robertson S. A method to inform team sport training activity duration with change point analysis. PLOS ONE. 2022; 17: e0265848. https://doi.org/10.1371/journal.pone.0265848 PMID: 35312735

27. Robertson S, Spencer B, Back N, Farrow D. A rule induction framework for the determination of representative learning design in skilled performance. J Sports Sci. 2019; 37: 1280–1285. https://doi.org/10.1080/02640414.2018.1555905 PMID: 30574842

28. Browne P, Sweeting AJ, Robertson S. Modelling the Influence of Task Constraints on Goal Kicking Performance in Australian Rules Football. Sports Med—Open. 2022; 8: 13. https://doi.org/10.1186/s40798-021-00393-9 PMID: 35072811

29. Pol R, Balagué N, Ric A, Torrents C, Kiely J, Hristovski R. Training or Synergizing? Complex Systems Principles Change the Understanding of Sport Processes. Sports Med—Open. 2020; 6: 28. https://doi.org/10.1186/s40798-020-00256-9 PMID: 32661759

30. Landis JR, Koch GG. The Measurement of Observer Agreement for Categorical Data. Biometrics. 1977; 33: 159–174. https://doi.org/10.2307/2529310 PMID: 843571

31. R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing; 2019. https://www.R-project.org/

32. Frencken W, Lemmink K, Delleman N, Visscher C. Oscillations of centroid position and surface area of soccer teams in small-sided games. Eur J Sport Sci. 2011; 11: 215–223. https://doi.org/10.1080/17461391.2010.499967

33. Hahsler M, Grün B, Hornik K. arules—A Computational Environment for Mining Association Rules and Frequent Item Sets. J Stat Softw. 2005; 14: 1–25. https://doi.org/10.18637/jss.v014.i15

34. Agrawal R, Srikant R. Fast algorithms for mining association rules. Proc 20th int conf very large data bases, VLDB. 1994. pp. 487–499.

35. Therneau T, Atkinson B. rpart: Recursive Partitioning and Regression Trees. 2022. https://CRAN.R-project.org/package=rpart

36. Aguiar M, Gonçalves B, Botelho G, Lemmink K, Sampaio J. Footballers' movement behaviour during 2-, 3-, 4- and 5-a-side small-sided games. J Sports Sci. 2015; 33: 1259–1266. https://doi.org/10.1080/02640414.2015.1022571 PMID: 25782702

37. Rothwell M, Davids K, Stone J, O'Sullivan M, Vaughan J, Newcombe D, et al. A department of methodology can coordinate transdisciplinary sport science support. J Expert. 2020; 3: 55–65.

38. Seifert L, Komar J, Barbosa T, Toussaint H, Millet G, Davids K. Coordination Pattern Variability Provides Functional Adaptations to Constraints in Swimming Performance. Sports Med. 2014; 44: 1333–1345. https://doi.org/10.1007/s40279-014-0210-x PMID: 24895244

39. Crang ZL, Duthie G, Cole MH, Weakley J, Hewitt A, Johnston RD. The inter-device reliability of global navigation satellite systems during team sport movement across multiple days. J Sci Med Sport. 2022; 25: 340–344. https://doi.org/10.1016/j.jsams.2021.11.044 PMID: 34893434

40. Johnston RJ, Watsford ML, Kelly SJ, Pine MJ, Spurrs RW. Validity and Interunit Reliability of 10 Hz and 15 Hz GPS Units for Assessing Athlete Movement Demands. J Strength Cond Res. 2014; 28: 1649–1655. https://doi.org/10.1519/JSC.0000000000000323 PMID: 24276300

41. Linke D, Link D, Lames M. Validation of electronic performance and tracking systems EPTS under field conditions. PLOS ONE. 2018; 13: e0199519. https://doi.org/10.1371/journal.pone.0199519 PMID: 30036364

VICTORIA UNIVERSITY

THE NEW WAY TO DO UNI

OFFICE FOR RESEARCH TRAINING, QUALITY AND INTEGRITY

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)

Title of Paper/Journal/Book: Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0278644

Surname: Teune First name: Ben

Institute: Institute for Health and Sport Candidate's Contribution (%): 75

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 02/12/2022

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] 06/12/2022

Signature **Date**

3. CO-AUTHOR(S) DECLARATION

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

The undersigned certify that:

1. They meet criteria for authorship in that they have participated in the conception, execution or interpretation of at least that part of the publication in their field of expertise;
2. They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;

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

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

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 storage space maintained by Victoria University.

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Carl Woods	5	Assisted with theoretical positioning, feedback and revisions	[redacted]	18/07/22
Alice Sweeting	5	Assisted with methodology, feedback and revisions		19/07/22
Mathew Inness	5	Assisted with feedback and revisions		26/07/22
Sam Robertsons	10	Assisted with concept and study design, feedback and revisions		27/07/22

Updated: September 2019

Evaluating the influence of a constraint manipulation on technical, tactical and physical athlete behaviour

7.1 Abstract

Evaluating practice design is an important component of supporting skill acquisition and improving team-sport performance. Constraint manipulations, including creating a numerical advantage or disadvantage during training, may be implemented by coaches to influence aspects of player or team behaviour. This study presents methods to evaluate the interaction between technical, tactical and physical behaviours of professional Australian Football players during numerical advantage and disadvantage conditions within a small-sided game. During each repetition of the game, team behaviour was manually annotated to determine: *repetition duration*, *disposal speed*, *total disposals*, *efficiency*, and *disposal type*. Global Positioning System devices were used to quantify tactical (*surface area*) and physical (*velocity* and *high intensity running*) variables. A rule association and classification tree analysis were undertaken. The top five rules for each constraint manipulation had confidence levels between 73.3% and 100%, which identified the most frequent behaviour interactions. The classification tree included three behaviour metrics and identified two unique movement solutions for each constraint manipulation. These results may inform if player behaviour is achieving the desired outcomes of a constraint manipulation, which could help practitioners determine the efficacy of a training task. Sport practitioners can adapt these methods to evaluate constraint manipulations and inform practice design.

7.2 Introduction

Practice is a crucial part of athlete development, supporting learning and performance (Davids et al., 2008). Sport coaches should therefore consider the design of practice tasks and activities which most effectively achieve their goals, whilst facilitating skill acquisition (Chow, 2013; Woods, McKeown, Rothwell, et al., 2020). A pedagogical approach, which may be used by practitioners to support the design of practice tasks, is constraint manipulation (Chow, 2013; Renshaw & Chow, 2019). Constraints represent boundaries or limitations to an athlete's interactions with their environment and the task being performed (Newell, 1986). Constraint manipulations have been effective at guiding movement exploration and enhancing skill development in baseball batting (R. Gray, 2020) and swimming (Komar et al., 2019). Specifically, in team sports, constraints such as field size or task rules, may be modified to guide the intentions, perceptions and actions of athletes while performing a practice task (Seifert et al., 2017). Athletes therefore must adapt their tactical (e.g. spatiotemporal movements), physical (e.g. distance and speed of locomotion), and/or technical (e.g. ball passing movements) behaviours to form movement solutions which aim to satisfy the constraints of a given task (Torrents et al., 2016).

Evaluating the influence of a constraint manipulation on athlete behaviour is useful to understand efficacy and potentially support practitioners in designing practice tasks (Teune, Woods, et al., 2021a). The effect of constraint manipulations, including field size (Fleay et al., 2018; Nunes et al., 2021; Timmerman et al., 2017), the number of players (Bonney et al., 2020; Timmerman et al., 2019; Vilar et al., 2014) and task rules (Correia et al., 2012; Timmerman et al., 2019; Travassos et al., 2014), on multiple facets of team and athlete behaviour, have been examined. To exemplify, field size manipulations can influence the collective coordination of players on the same and opposing teams (Frencken et al., 2013; Travassos et al., 2014). Field size is also positively related to the physical output of players and can be negatively related to the frequency of some technical actions, such as tackles or passes, in Australian football (AF) and field hockey (Fleay et al., 2018; Timmerman et al., 2017). However, the interactions between a wider range of player behaviours, including technical, tactical and physical attributes, when manipulating constraints in AF training remains to be explored.

The constraints-led approach is a conceptual framework which advocates for constraint manipulation to facilitate skill development (Davids et al., 2008; Renshaw & Chow, 2019). According to the constraints-led approach, constraints do not act in isolation but interact with one another, often in a non-linear manner (Chow, 2013). Thus, a challenge for practitioners is to understand how the manipulation of a single constraint can impact the many facets of an athletes performance (Balagué et al., 2019). Accordingly, it is pertinent to measure constraint interaction in order to provide appropriate contextual information when evaluating player behaviour (Browne et al., 2020; Browne, Sweeting, et al., 2019). Importantly, contextualising constraint interactions highlights how the expression of a constraint changes when considered alongside other constraints. Further, from an applied perspective, the constraints-led approach has been suggested as an appropriate framework to support inter- and multi-disciplinarity in high performance support teams (Browne et al., 2021; Glazier, 2017). For example, evaluating the skilled and physical output of athletes, associated with constraints manipulation in practice tasks, can foster interaction and collaboration between high performance and sports coaching staff (Corbett et al., 2018; Teune et al., 2022). To this end, tools or methods which can support practitioners to evaluate constraint interaction may enhance their training design.

Multivariate analytical techniques are advantageous for understanding constraint interaction (Browne et al., 2021; Browne, Sweeting, et al., 2019). Multivariate techniques, including rule association or classification and regression trees, have been applied to evaluate AF match kicking (Browne, Sweeting, et al., 2019; Robertson et al., 2019a), goal kicking (Browne et al., 2022) and skilled actions during training activities (Teune, Woods, et al., 2021a). The advantages (and disadvantages) of these analytical approaches have been discussed regarding the prevalence of constraints during AF goal kicking (Browne et al., 2022). Specifically, the interpretability and flexibility of analytical outputs should be considered to suit the needs of coaches and facilitate practical implementation of findings. Accordingly, the application of these techniques to inform team sport training design may be beneficial. Methods or tools which can inform training design may support practitioners' decision making by condensing the volume of information required to consider complex constraint interactions (Browne et al., 2021; Pol et al., 2020). Thus, the current study aimed to demonstrate methods to evaluate the influence of a numerical constraint manipulation on the interaction between technical, tactical and physical player behaviour.

7.3 Methodology

7.3.1 Participants

Participants were a convenience sample of professional players from one AF club (n = 41, height = 187.7 ± 8 cm, mass = 84.4 ± 8.6 kg, age = 24.7 ± 3.8 years). All players were injury free at the time of participation. Ethics approval was obtained from the Victoria University Human Research Ethics Committee (application number: HRE20-138). Written consent was provided by the club to use de-identified data collected from the participants, as regular procedure during practice.

7.3.2 Data Collection

Data were collected for a single training task repeated (n=69) throughout the 2022 Australian Football League pre-season training period (November 2021 – February 2022). Team selection was quasi-randomised by coaching staff on each occasion to balance team skill level. The training task comprised a small-sided game involving two teams of players competing against each other on a field approximately 85 m x 65 m. The aim of the task was to move the ball from one end of the field to the other, while the defending team aimed to oppose this ball movement. A team number constraint was manipulated by coaches whereby one team of seven competed against a team of eight, providing each team with either a numerical advantage (plus one) or disadvantage (minus one). At the halfway point during each training session, the conditions were swapped so that both teams experienced each numerical constraint manipulation, in attack and defence. Task repetitions were defined by the sequences of play during the training activities, beginning with the ball at one end of the field until completion with the ball at the opposite end. Accordingly, repetitions were collected for both the numerical advantage (*n* = 32) and the disadvantage (*n* = 37) conditions.

To collect data pertaining to the technical skill of the players, the training activities were filmed from a side-on and behind-the-goals perspective with a two-dimensional camera (Canon XA25/Canon XA20). The two angles were subsequently aligned after the session for manual annotation. Skill data were collected via notational analysis software (Hudl Sportscode v12.4.2) using the aligned vision. Each pass (or "disposal") was manually coded according to the type (kick or handball) and effectiveness (effective or ineffective). A kick or handball < 40 m, in which the intended target retained possession of the ball, or a kick > 40 m to a 50/50 contest or advantage to the attacking team, was deemed effective, in accordance with Champion Data (Melbourne, Pty Ltd), the commercial statistics provider for the Australian Football League. A single coder notated this information. Thus, intra-rater reliability was examined via the kappa statistic (Landis & Koch, 1977), with a 14 day intra-reliability test resulting in "almost perfect" agreement (0.95). Using this information, the efficiency, percentage of kicks, disposal count and disposal speed were calculated for each repetition (Table 7.1).

Table 7.1 Player behaviour metrics and associated definitions. 1SD = one standard deviation.

Type	**Metric**	**Definition**
Technical	Efficiency (%)	Percentage of effective disposals to total disposals
	Percentage Kicks (%)	Percentage of kicks to total disposals
	Total disposals (#)	Total number of disposals performed
	Repetition duration (s)	Time from beginning to end of repetition
	Disposal speed (disp/min)	Total disposals divided by repetition duration in minutes
Tactical	Surface Area (m^2)	Average surface area of attacking team minus average surface area of defending team
	1SD Surface Area (m^2)	Standard deviation of surface area of attacking team minus standard deviation of surface area of defending team
Physical	Velocity (m/min)	Average velocity of attacking team minus average velocity of defending team
	1SD Velocity (m/min)	Standard deviation of velocity of attacking team minus standard deviation of velocity of defending team
	HIR (m/min)	Average HIR metres per minute of attacking team minus average HIR metres per minute of defending team
	1SD HIR (m/min)	Standard deviation of HIR of attacking team minus standard deviation of HIR of defending team

To determine tactical and physical movement of players during the training tasks, spatiotemporal positioning and velocity of each participant was collected using 10 Hz Global Positioning System devices (Vector S7, Catapult, Catapult Sports Ltd, Melbourne) which were placed on the participant's back, between their shoulder blades. Each participant wore the same device during all activities to reduce inter-unit error. After session completion, tracking data for each participant was downloaded using the associated software (Openfield v 3.3.1) and exported for analysis. This data comprised latitude, longitude and velocity values at each 10 Hz timestamp for each participant. Each participant's tracking data was then down sampled to a rate of 1 Hz by taking the mean latitude, longitude, and velocity across every ten fixed samples. This was done to simplify the subsequent merging process with skill event data. This, and all subsequent data analysis, was completed using the *R* programming language (R Core Team, 2019) with the *RStudio* software (v2021.09.2).

Participant spatiotemporal data then was used to determine the surface area of each team during each task repetition. All latitude and longitude data were first converted to x and y coordinates, in metres, relative to the minimum x and y values in the dataset. Surface area was then calculated, at each 1 Hz time point, by determining the area (m^2) between the outermost players, also known as a convex hull (Frencken et al., 2011). For each repetition, the mean and one standard deviation (1SD) of the surface area was determined for the attacking and defending team. These values were then converted to a differential between the attacking and defending team.

The tracking data was also used to determine the velocity and high intensity running (HIR) metres of each team during each repetition. The mean velocity was calculated for each player during each repetition and represented as $m \bullet min^{-1}$. These values were then used to determine the mean and 1SD in velocity for the attacking and defending team during each repetition. Similarly, HIR was calculated for each repetition, defined as any running speed > 250 $m \bullet min^{-1}$ (15 km/h). Mean HIR was calculated for each player during each repetition and represented as $m \bullet min^{-1}$. These values were then used to determine the mean and 1SD in HIR for each team during each repetition. Mean velocity, velocity 1SD, mean HIR, and HIR 1SD were represented as a differential between the attacking and defending team.

7.3.3 Statistical Analysis

A correlogram was used to explore any univariate linear relationships between behaviour metrics. To determine the influence of the team number constraint manipulation on player behaviours, two multivariate analytical approaches were applied: rule association and classification trees. To apply rule association, each behaviour metric was first discretised into three arbitrary categories: low, medium and high. These categories were chosen to align with the preferences of the end-users (i.e., coaches of the football club). This was achieved using the *discretizeDF* function in the *arules* package (Hahsler et al., 2005), using a cluster method set for three groups. Rules for each numerical condition were then generated using the *apriori* function, which uses the *Apriori* algorithm (Agrawal & Srikant, 1994). For each numerical condition (advantage and disadvantage) parameters were set to a minimum support of 0.15, minimum confidence of 0.7, and a minimum rule length of four.

The second approach applied a classification tree using the *rpart* package (Therneau & Atkinson, 2022). The *rpart* function was used to classify the numerical condition of each task repetition based on the values of the behaviour metrics. The default parameters for the function were used with a complexity parameter of 0.01, a minimum split attempt of 29% (20 observations) and minimum terminal node observations set at seven (minimum split / 3).

7.4 Results

For the 32 numerical advantage repetitions, the mean duration was 16.3 s ± 8.2 s and the mean disposal count was 2.9 ± 1.3. For the 37 numerical disadvantage repetitions, the mean duration was 22.7 s ± 12.8 s and the mean disposal count was 3.6 ± 1.6. The distribution of each metric, within each condition is displayed in Figure 7.1. The correlogram was presented in Figure 7.2. Univariate correlations between all behaviour metrics were within 0.5 and -0.5 with the exception of positive correlations between total disposals and repetition duration (0.84) and between velocity and HIR (0.8).

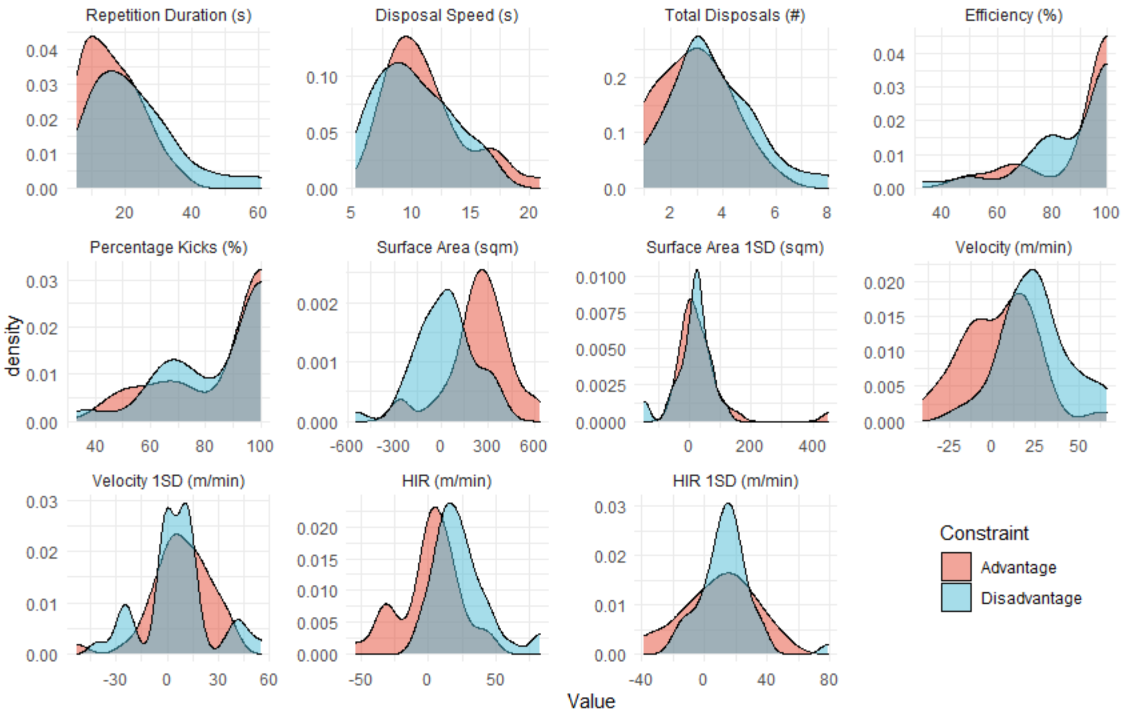


Figure 7.1 Distribution of each behaviour metric within advantage and disadvantage constraint conditions.

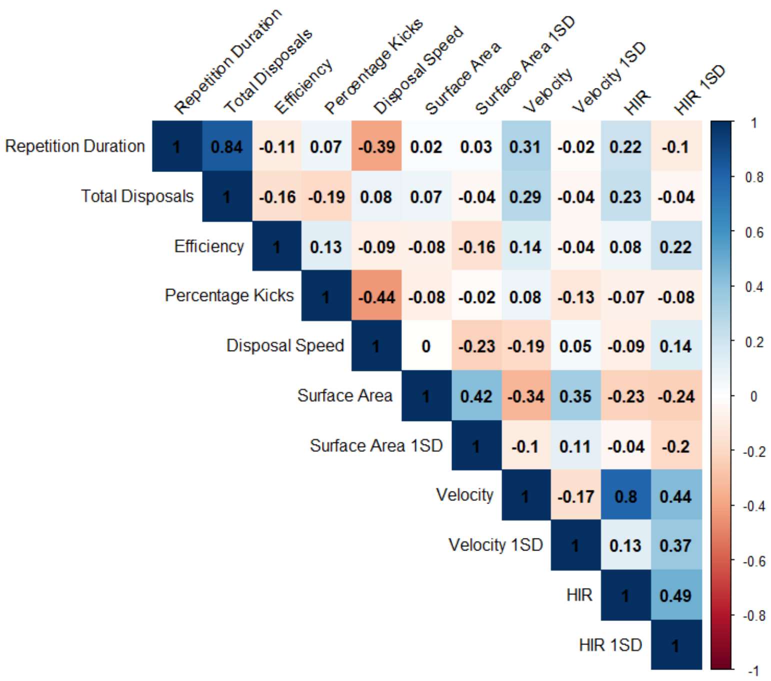


Figure 7.2 Correlogram of each behaviour metric.

For the rule association approach, the resulting cut-off values used during discretisation are displayed in Table 7.2 and the counts within each category of the discretisation are displayed in Figure 7.3. From the results of the *Apriori* algorithm, nine rules were generated for the numerical advantage condition and six rules were generated for the numerical disadvantage condition. The top five rules, by confidence, for each condition are displayed in Figures 7.4 and 7.5. Confidence measures the frequency of the constraint condition given the associated ruleset. For the numerical advantage condition, confidence ranged from 80% to 100% and for the numerical disadvantage condition, confidence ranged from 73.3% to 85.7%.

Table 7.2 Cut-off values used to discretise each behaviour metric.

Metric	Low	Med	High
Repetition Duration (s)	< 18.3	18.3 to 38.2	> 38.2
Total Disposals (#)	< 2.29	2.29 to 3.89	> 3.89
Disposal Speed (disp/min)	< 10	10 to 14.2	> 14.2
Efficiency (%)	< 61.3	61.3 to 88	> 88
Percentage Kicks (%)	< 69.3	69.3 to 88.8	> 88.8
Surface Area (m^2)	< -28.3	-28.3 to 237	> 237
Surface Area 1SD (m^2)	< 11.7	11.7 to 250	> 250
Velocity (m/min)	< 3.61	3.61 to 36.7	> 36.7
Velocity 1SD (m/min)	< -8.95	-8.95 to 21.5	> 21.5
HIR (m/min)	< -11.7	-11.7 to 27.1	> 27.1
HIR 1SD (m/min)	< 0.46	0.46 to 27.2	> 27.2

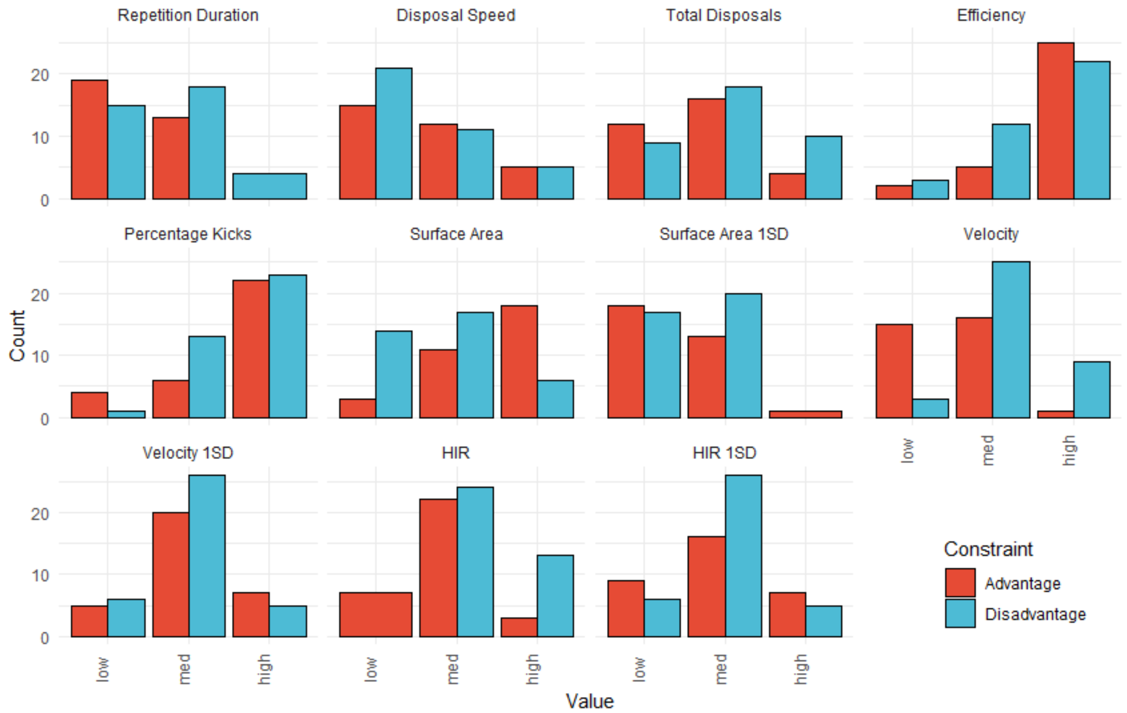


Figure 7.3 Results of the discretisation of each behaviour metric. Repetition counts for each category are displayed for the advantage and disadvantage constraint conditions.

	Tactical		Physical				Technical					
	Surface Area	Surface Area 1SD	Velocity	Velocity 1SD	HIR	HIR 1SD	Repetition duration	Total Disposals	Disposal Speed	Efficiency	Percentage Kicks	Confidence
1	high			med	med							100%
2			low				low	low				84.6%
3	high				med		med					84.6%
4	high				med	med				high		84.6%
5	high				med					high		80%

Figure 7.4 The top five rules generated for the advantage constraint condition, ordered by confidence. Each discretised metric is colour coded according to its category for visual interpretability.

	Tactical		Physical				Technical					
	Surface Area	Surface Area 1SD	Velocity	Velocity 1SD	HIR	HIR 1SD	Repetition duration	Total Disposals	Disposal Speed	Efficiency	Percentage Kicks	Confidence
1	med		med	med								85.7%
2		med	med						low			84.6%
3		med				med	med					75%
4			med	med					low			73.3%
5				med		med			low			73.3%

Figure 7.5 The top five rules generated for the disadvantage constraint condition, ordered by confidence. Each discretised metric is colour coded according to its category for visual interpretability.

The resulting model for the classification tree is displayed in Figure 7.6. The only variables used by the model to partition the data were surface area, repetition duration and velocity 1SD. Four terminal nodes are shown, two for each numerical condition with classification accuracies ranging from 71% to 94%. A visualisation of all behaviour metrics within each terminal node, scaled to allow comparison, was also provided (Figure 7.7).

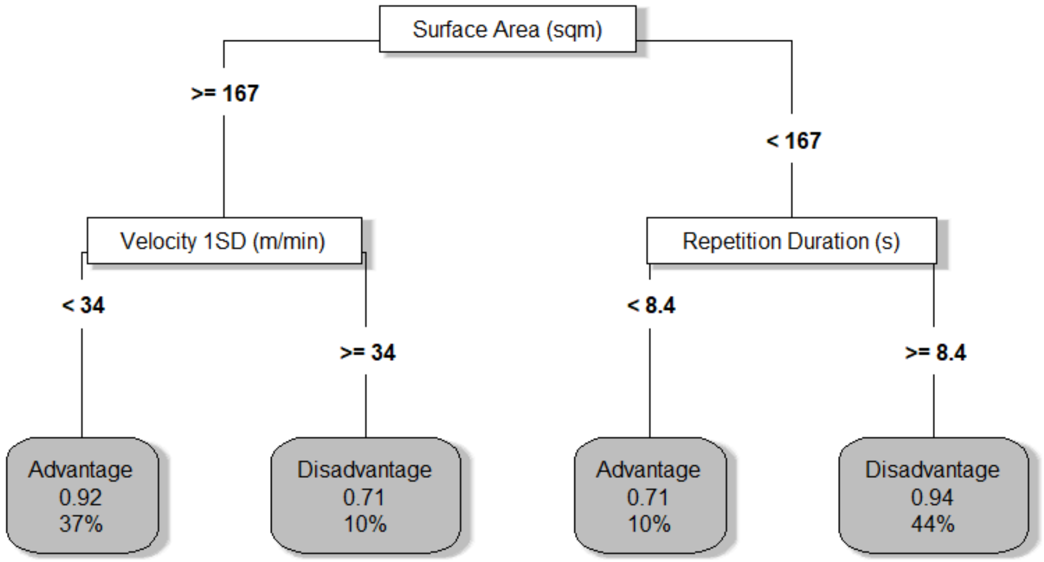


Figure 7.6 The classification tree used to model the constraint condition (advantage or disadvantage). Terminal nodes are labelled with the predicted constraint condition while the decimals indicate the accuracy of the fitted value and the percentages indicate the accuracy of the fitted value and the percentages indicate the frequency of observations.

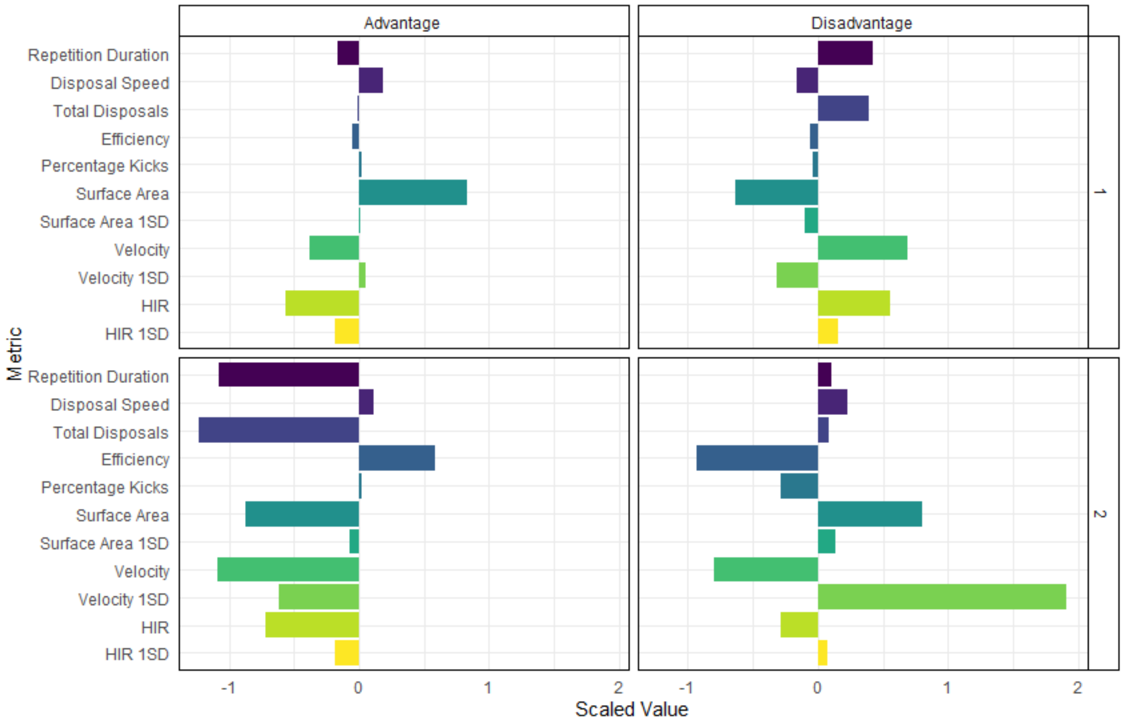


Figure 7.7 The average of each behaviour metric within the identified task solutions (1 and 2) for each constraint condition (advantage and disadvantage). The bar plot values are scaled to a mean of zero and a standard deviation of one to allow comparability between metrics.

7.5 Discussion

The aim of this study was to demonstrate methods to evaluate a numerical constraint manipulation while considering the interaction of player technical, tactical and physical behaviour. A rule association and classification tree approach were used to analyse player behaviour, under the premise of supporting practice task design in team sport. The rule association provided a simple visualisation whereby coaches can identify associations between aspects of player behaviour. Additionally, the classification tree could be used to determine specific values of interest which can guide ongoing constraint manipulations in practice task designs.

The results of the rule association analysis provide a simple heuristic to support coach decision-making. The rules displayed in Figures 7.4 and 7.5 highlight which simultaneous behaviours players are exploiting to achieve the given task. This builds upon previous AF work using rule association to evaluate training (Teune, Woods, et al., 2021a) and match play (Browne, Sweeting, et al., 2019; Robertson et al., 2019a) through the inclusion of tactical and physical behavioural metrics. Moreover, the rule association identified non-linear relationships between behaviour metrics which were not determined in the linear exploration shown in Figure 7.2. Discretising continuous variables is a necessary step to perform rule association and presents both advantages and disadvantages for interpretation. Binning values into three categories; low, medium and high, may suit the communication preferences of coaches although, other quantities of bins may also be used. Decisions on bin quantities should be aimed at improving the coaches' ease of use and increasing the speed of their decision making, which therefore may vary. However, discretisation can reduce the explanatory power of continuous variables. For example, a range of values can be identified within each category but no specific values for player behaviour can be provided to the practitioner, limiting their utility for intervention.

The results of the rule association suggest, that when playing with a numerical advantage, teams used their additional player to spread over larger areas than their opposition. This was indicated as four of the five top rules for the advantage condition included high levels of surface area. Additionally, within each of these four rules, high surface area was associated with medium levels of HIR. This may suggest that this level of physical running speed was required to achieve the levels of high surface area. Other metrics, including kick percentage and disposal speed, were not included in any of the top five rules. This indicated that the numerical advantage did not influence these behaviours, nor did they interact with others at a meaningful level. Contrastingly, in the numerical disadvantage condition, three of the top five rules involved low disposal speed. A team at disadvantage frequently exhibited a slower speed of play. Low disposal speed was also associated with medium surface area 1SD, medium velocity and medium velocity 1SD. Similar findings in investigations of other constraint manipulations, such as field density or team size, have reported simultaneous changes to skilled, physical and tactical behaviour of players in field hockey and soccer (Aguiar et al., 2015; Timmerman et al., 2017) however, their interactions were not determined. In the current study, results of the rule association showed how interactions between the behaviours of players can be measured. Accordingly, these interactions are pertinent information for both a conditioning and skills coach. For example, a conditioning coach can monitor and prepare players for the specific work rates required to perform tactical manoeuvres influenced by the numerical constraint manipulation. This outcome highlights how the analysis can provide a platform for a multidisciplinary approach to support athlete development (Browne et al., 2021; Rothwell et al., 2020).

In further results of the rule association, the second rule for the numerical advantage condition presented three unique variables, absent in any other rules, consisting of low repetition duration, low total disposals and low velocity. This indicates an alternate task solution was used by the players. In this solution, the ball is moved quickly down the field with a low quantity of disposals and lower running speed than the defence. This observation is similar to other work in AF, in which the inclusion of an additional attacker reduced the average velocity of the group (Bonney et al., 2020). This solution may emerge given a sudden exploitation of an opportunity, such as a lapse in defensive structure. Depending on the training objectives of coaches, training design may be modified to encourage or discourage performance of this solution. For example, to discourage this solution and further guide player's attention toward using their numerical advantage to maximise surface area, an additional task constraint of a minimum pass count could be implemented during the advantage condition.

Contrasted with rule association, the classification tree could be advantageous by enabling the data to be modelled in its continuous format. Accordingly, when using numerical data, critical values can be directly provided by the model which are influential on player behaviour. To exemplify, along the right branch of the tree (Figure 7.6), a common task solution for the numerically disadvantaged team was to slow the sequence of play down as indicated by the repetition duration of >8.4 s. This behaviour may have emerged as players sought additional time to create space against a team possessing an extra number, thereby maintaining possession of the ball. The repetition duration value of 8.4 s may be leveraged by a coach seeking to encourage greater exploration in task solutions. For example, a temporal constraint of 8 s may be introduced to challenge the stability of this solution for the team with the numerical inferiority. This may lead to the emergence of a new behavioural pattern, as players search to exploit both the numerical inequality and temporal constraint. Only three behaviours were found to be influenced by manipulation of the numerical constraint: surface area, velocity 1SD and repetition duration. This suggested that all other behaviours remained predominantly stable despite the numerical constraint manipulation. Using this information, coaches may choose to manipulate additional constraints, such as field dimensions or task rules, to perturb player behaviours and encourage variability (Seifert et al., 2014).

The partitions provided by the classification tree may be used to identify the different task solutions performed by teams within each numerical constraint. A similar approach has been reported in swimming where a clustering analysis identified if learners were exploiting or exploring task solutions during training (Komar et al., 2019). In the current study, the classification tree produced two terminal nodes for each numerical condition, suggesting two unique task solutions were exhibited within each constraint. The first solution was the most frequently used (advantage = 37%, disadvantage = 44%) and the second solution was the least frequently used (advantage = 10%, disadvantage = 10%). Figure 7.7 can thus highlight how technical, tactical and physical behaviours are organised simultaneously by teams to achieve the task goal. This may be advantageous as a complementary visualisation to the classification tree, reporting all behaviour metrics in addition to the three included in the classification tree. Thus, through evaluations of these behaviours, coaches may seek to guide or nudge players towards new or more optimal task solutions, according to their training objectives (Woods, McKeown, Rothwell, et al., 2020).

Given the applied nature of the current study, some limitations exist which should be considered. Field sizes were approximately measured during data collection and some small variations may exist between training sessions. This, however, was controlled as closely as practically possible. Additionally, while players on each team were selected to balance skill level, player selection was inconsistent across each session. Accordingly, these factors may have influenced team behaviours between task repetitions. Some instances occurred where there was an unused player on the sideline (due to irregular numerical grouping) and players were permitted to substitute between repetitions, which may have influenced the physical output of players. From an analytical perspective, only one measure of tactical behaviour was used during this study and future work may be directed to include other measures of collective team behaviour, such as centroid location, difference between team centroids, or team separateness. Finally, future work may seek to measure constraints on disposals, such as pressure or possession time, to provide further context to the technical actions performed during repetitions. The results, nonetheless, provide an enticing methodological platform for future work.

7.6 Conclusion

This study applied two multivariate analytical techniques, rule association and a classification tree, to evaluate the influence of a numerical advantage or disadvantage on the technical, tactical and physical behaviour of AF players during a small-sided training task. The rule association approach presented a simple and interpretable output for coaches which informed interactions between key behaviours during each constraint condition. The classification tree provided specific values of interest which may be used to inform further constraint manipulations to enhance practice task design. A visualisation of the different task solutions identified through the classification tree was provided to assist coaches in evaluating how players organise their movements within each constraint. These methods and visualisations are provided as tools which sport practitioners are encouraged to adopt to inform the design of their own training activities.

CHAPTER EIGHT – GENERAL DISCUSSION AND CONCLUSION

Chapter Overview

This chapter consolidates key findings of this thesis and discusses the broader implications for the sports industry and the practical applications for practitioners.

8.1 General discussion

This thesis aimed to provide tools and methods to support sport practitioners with the design of practice tasks. While AF was used as the exemplar sport, the findings may be extended to other team invasion sports. Throughout the thesis, the CLA was used as the major theoretical framework with guiding principles for facilitating skill acquisition (Davids et al., 2008). Given constraint interaction was identified as a key tenet underpinning the CLA, various multivariate analytical techniques, including rule association and decision trees, were used to determine the interaction between various constraints during training activities.

The studies within this thesis supported how the CLA may be implemented in sport to support practice task design. First, Chapter Three sought to improve the measurement of the constraint of physical pressure, which influences skill performance, to gain insight into how this constraint could be designed into practice tasks. A continuous pressure measurement was developed, which showed a positive relationship with skill effectiveness, contrasting with the discrete measurement of this constraint. Chapters Four and Five demonstrated how practitioners may determine the influence of task, environmental and individual constraint interactions on skilled behaviour through the implementation of various machine learning algorithms. Rule association and regression trees evaluated player behaviour within training activities, identifying important constraint interactions which may inform a practitioner's training design. To further support practice design, a continuous time-series analysis – change point detection – was used to inform training activity duration (Chapter Six). Univariate and multivariate change point approaches identified critical time points in which player behaviour meaningfully changed, thereby indicating potential end times to activities. Finally, in Chapter Seven, the interaction between tactical team coordination, physical movement and technical skill behaviour was examined using rule association and classification trees. This was an exemplar method for evaluating constraint manipulations finding four different behavioural task solutions which can guide coaches in their ongoing constraint manipulations.

8.1.1 Implications for the sports industry

Broadly, supporting the practical implementation of the CLA, as presented in this thesis, may facilitate skill acquisition, leading to greater competitive performances of athletes and teams. The AFL, like other sport leagues globally, is a highly regulated competition. Though specific regulations may differ between competitions they may involve strict rules implicating things like the frequency of training sessions players are allowed to complete, and the amount of spending a club can allocate to the recruitment of coaching and performance staff. While these organisational constraints can be limiting, innovative practice through carefully considered sport science and coaching interventions, present opportunities to gain a performance advantage (Johnston et al., 2018). The practical application of techniques demonstrated in this thesis present such innovation, supporting sport practitioners and coaches to improve the design of their training activities, and increasing the effectiveness of their limited available training time. Improved training design may also complement other areas of sport organisations. For example, talent identification and recruitment may be accompanied by enhanced skill development processes, which for clubs unable to recruit the highest available talent, improved training design may expedite the skill development of currently rostered players. Further, appropriate training design may build upon the success of individual athlete recruitment by facilitating team cohesion, developing tactical skill acquisition to garner success at a team level.

A main goal for practice design is to foster conditions in which player skill is improved. It is common within professional high-performance sport, such as AF, for staff and player performance to be evaluated according to team match performances and end of season rankings. To this end, the structure and design of training environments represents one area of improvement which can have important, positive effects on match performance. Indeed, the transfer of skills from training to competition is critical and is a key tenet of the CLA as the guiding theoretical framework underpinning this thesis (Davids, 2014; Renshaw et al., 2010; Renshaw & Chow, 2019). The tools and techniques presented in this thesis, although intended to enhance various aspects of training, carry the overarching objective of improving match performance. Thus, sporting organisations which adopt these methods may gain a performance advantage over their competition.

This thesis supports the decision making of team sport coaches who are challenged with potentially complex and multi-faceted tasks, such as training design (Correia et al., 2019; Cushion, 2007). Decision support systems are commonly used in sport environments and are critical to progressing the field to optimise the accuracy and speed of practitioners' decision making (Robertson, 2020; Robertson et al., 2017). Two advantages to decision support within the current thesis are proposed. Firstly, objective analysis of data may provide an unbiased perspective to player or team evaluations, which may help overcome human cognitive limitations, such as heuristics or biases (Schelling & Robertson, 2020). Secondly, data analysis techniques, such as rule association or decision trees, can determine complex non-linear interactions within large datasets and over long periods of time. This is important as large, multivariate datasets are increasingly common in high performance sport (Rein & Memmert, 2016), and human decision making processes are less capable of handling such large volumes of information (Robertson & Joyce, 2019). However, this thesis does not call for coach subjectivity to be replaced by the analytical techniques presented, but to be better supported and complemented by them (Bartlett, 2001; McIntosh et al., 2019). Thus, an appropriate application of this thesis would emphasise the supporting role analytical tools play in practice design, presenting coaches with user-friendly visualisations that support, challenge or extend their experiential knowledge (Woods, Araújo, et al., 2021). For example, Chapter Six identified critical time points during a training activity where player behaviour meaningfully altered. This information may be used to direct the attention of coaches to this time period, supporting their perception of behavioural changes in their players and potentially informing further constraint manipulations. In another example, the analytical tools presented in Chapter Seven may support how practitioners determine the efficacy of a constraint manipulation. However, these techniques can not directly inform a coach which further constraint manipulations should be implemented to improve the training design. Thus, implementation of this thesis is intended to support, not replace, key decision makers such as coaches.

The tools presented within this thesis can also encourage collaboration between sport disciplines. Promoting inter-disciplinarity in sport may be advantageous to enhance the application of sport science (Browne et al., 2021; Rothwell et al., 2020; Woods, Rudd, Araújo, et al., 2021). To compete in elite team sport, athletes require many well-developed qualities including physical, both strength and aerobic, and technical and tactical skills. One way to facilitate the development of such qualities is through the implementation of sport training activities, such as small sided games, given their representation of competition interactions (Corbett et al., 2018; Farrow et al., 2008; Gabbett et al., 2009). The design of such activities would benefit from collaboration between multiple high-performance staff, including strength, conditioning, technical and tactical coaches. Practice design, thus, should be addressed in a multi-disciplinary manner to improve multiple athlete qualities. However, multi-disciplinary teamwork has faced challenges in applied sport science – none more apparent than disciplinary siloing (Rothwell et al., 2020). This thesis supports multi-disciplinary operation through the integration of data types relating to various aspects of athlete performance, such as skill event data and physical output data. For example, in Chapter Six, skill and physical data were analysed together to examine how player behaviour may alter during a training activity. Exemplar visualisations were provided as a platform where physical conditioning and skill coaches may collaborate to uncover unique solutions which achieve their goals together. In a specific example from Chapter Seven, during a small-sided game, teams exploited the advantage of their additional player by exhibiting medium levels of high intensity running to spread over a larger physical area than their opposition. Accordingly, this interaction of tactical manoeuvres and physical output is pertinent information for both the skills coach and the conditioning staff, allowing them to measure how tactical decisions may influence the physical output of players and vice-versa. Understanding this interaction is helpful when evaluating the efficacy of constraint manipulations.

Further inter-disciplinary insights may be gained via the techniques in this thesis as they permit blurring of the boundaries between disciplinary metrics, such as physical output and technical skill executions. For example, high intensity running volumes may be indicative of (un)skilful running patterns, while technical kicking actions may also be viewed as a type of physical load experienced by players. Accordingly, enhanced insights may be gleaned by various disciplinary staff through the sharing of such information, via exemplar platforms presented in this thesis. In other broader applications, more data types relating to other aspects of performance could also be integrated within these analyses. For example, constraints such as joint kinematics or emotions could be measured and included within the same models. This would permit wider interactions to be understood when evaluating training design and may help to further improve a diverse range of athlete qualities. For example, measuring emotion may inform constraint manipulations which enhance athlete enjoyment, or contrastingly expose athletes to stressful match-like situations, while maintaining the desired physiological or skill training targets. This data may also inform session structures, such as prescribing high enjoyment activities prior to matches to support athlete confidence. Such outcomes will become more feasible in the future as technology which can automatically collect this data, such as inertial measurement sensors or computer vision, is more widely implemented.

In this thesis, AF was used as an exemplar sport, however, the applications may be extended to other AF teams and other sports, with particular commonalities drawn between team sports which facilitate its translation. Practically, similar data capture technologies, such as tracking devices (Gudmundsson & Horton, 2017; Gudmundsson & Wolle, 2014) and video notation software (Rein & Memmert, 2016; Stein et al., 2017) are used across multiple sports. Theoretically, the application of the CLA as a guiding framework for training design has also been explored in other sports such as Rugby Union (Pocock et al., 2020), American football (Yearby et al., 2022) and soccer (Davids et al., 2013). It is recommended that practitioner's experiential knowledge be used to guide adaptation of the tools within this thesis to different sports, such as informing the key constraint measurements which influence player performance (Greenwood et al., 2014; Pocock et al., 2020). For example, the key constraints influencing Rugby Union place kicking such as wind, score margin, fatigue, and distance and angle to goalposts (Pocock et al., 2020) could be included in rule association or decision trees models, as demonstrated in the current thesis, to determine any non-linear constraint interactions. This may help practitioners profile players with constraint sets related to unsuccessful kicks which may then inform their training design. Thus, adaptations of the techniques demonstrated in this thesis would allow practitioners to model the key constraint interactions relevant to their own sport training environments. Moreover, the analytical techniques presented in this thesis are adaptable to achieve broader sporting applications. For example, given the sequential nature of sport at many organisational levels, change point detection (Chapter Six) may have a range of useful applications. In sports with congested schedules, such as basketball or baseball, change point analysis may inform appropriate practice periods by identifying time points of lower schedule intensity, such as periods of decreased opposition quality and reduced travel. Change point detection may also be applied to inform the design of injury rehabilitation sessions by identifying when athletes have progressed to the next phase of their rehabilitation plan. A continuous pressure measurement, demonstrated in Chapter Three, may be analysed during basketball match shooting to inform representative density levels during shooting practice. While in soccer, association rules or decision trees could be used to identify the key tactical and physical constraint interactions that facilitate goals, which can then be designed into practice tasks. In sum, many opportunities exist to adapt the tools demonstrated within this thesis for wider sporting applications.

8.1.2 Practical applications for sport practitioners

Two main themes for improving the application of the CLA are covered in this thesis: i) improved analysis of constraints, and ii) improved constraint measurement. To address the former, this thesis highlighted the importance of considering constraint interaction during training evaluation. Moreover, the studies of this thesis explored how constraint interaction may be analysed and presented in a meaningful way to practitioners in an applied sport setting. While constraint interaction has been recognised as theoretically important to sports performance (Balagué et al., 2019; Newell, 1986), in practice, it remains challenging to measure. This is due, in part, to the large volume of data and various types, such as player tracking or skill event data (Rein & Memmert, 2016), and the likely non-linearity of constraint interaction, which increases the complexity of determining constraint influence (Chow, 2013; Davids, 2012). With these challenges in mind, this thesis provided tools to support practitioners in understanding constraint interactions to inform their training design.

Through the utilisation of machine learning techniques, such as rule association or regression trees, it was possible to determine how constraints manipulated during training, such as field size or task rules, interacted to influence athlete behaviour. For example, Chapter Four revealed the most prevalent sets of constraints that influenced possession time and pressure (Table 4.2) which can guide how coaches manipulate these constraint sets to increase or decrease levels of possession time and pressure. Although a broad range of literature has investigated the isolated influence of single constraint manipulations (for reviews in soccer see Ometto et al., 2018; Sarmento et al., 2018), few studies have determined how constraint interaction occurs. This is a limitation for coaches as they may over or under value the influence of a constraint without consideration of its interactive nature within a larger set of constraints. For example, in Chapter Five, athlete experience was only an influential constraint when considered within training activities which limited the disposal type to handballs. For this group of players then, the constraint of athlete experience should therefore be contextualised alongside the activity type to appropriately understand it's influence on training behaviour. Moreover, studies which have explored constraint interaction have been limited to bi-variate (Timmerman et al., 2019) or linear interactions (Pocock et al., 2018). This may be because the analytical approaches adopted in these investigations were not suited to determine multivariate, non-linear interactions. Accordingly, the studies within this thesis have built upon this work by exploring how multiple constraints may be considered together, using appropriate analytical techniques. Coaches may, therefore, be better informed as to the importance of considering constraint interaction during training design and how to measure it's influence on athlete behaviour and enhance skill development.

A second theme throughout this thesis, for improving the implementation of the CLA in sport, was the improved measurement of constraints. Chapters Three and Six explored how athlete behaviour could be continuously represented. In Chapter Three, for example, the constraint of physical pressure on skilled actions was represented in a continuous manner, which contrasted with previous discrete measurements (Browne, Sweeting, et al., 2019; Ireland et al., 2019; Robertson et al., 2019a). The advantages of the continuous measurement were that it permitted the consideration of multiple opponents throughout the entire field, not just within a specific perimeter. In a second approach, Chapter Six analysed the continuous time-series of physical and skilled behaviour of players during a small-sided training activity. This analysis provided more detailed insight than could be achieved from aggregate or grouped measures, as has been the approach in previous work (Black et al., 2016; Black, Gabbett, Naughton, et al., 2019; Sparks et al., 2016). Together, Chapters Three and Six demonstrated how the utilisation of technology and more sophisticated analytical techniques could be applied in sport to improve existing measures for constraints (Browne et al., 2021). This is important, as with the sports industry continuing to advance, the frequency and detail of data collection will increase (Rein & Memmert, 2016). Alongside this, advancements in computer processing power, coupled with new technologies, could further enhance the speed and accuracy of gathering and reporting data. Accordingly, there is growing opportunity to leverage these continued advancements to support coaches. Continuous measurements, therefore, will gain more and more value in their application, allowing for deeper insights to be reported from more detailed data.

Within high-performance sport, constraints exist at multiple scales and interact (Balague et al., 2013; Balagué et al., 2019; Ribeiro et al., 2019). Aligning with this, the tools presented within this thesis evaluate training design at multiple scales of analysis whereby, a combination of these tools may support various aspects of coach decision making. For example, at one level, inter-activity analyses explored the broad evaluation of many training activities, across weeks and seasons (Chapters Four and Five). This has application to inform high level session prescription (Corbett et al., 2018) or longitudinal training design (Farrow & Robertson, 2017) which a coach may use to guide general weekly or monthly planning. Chapter Five may also be implemented to determine any potential individual differences in player behaviour which should be accounted for during this process. At a second level, intra-activity analyses explored the specific evaluation of features occurring within single activities (Chapters Six and Seven). These studies explored more detailed aspects of acute athlete behaviour, such as pressure on skill involvements or fluctuations in skill efficiency. Thus, these tools may be suitable to support coaches to make in-session constraint manipulations or adjustments. When integrated, the various tools presented across this thesis offer a multi-faceted approach to inform training design.

Across the studies in this thesis, the flexibility and adaptability of analytical solutions was demonstrated. This aligns with other work in AF (Browne et al., 2022) and is highlighted as a beneficial outcome for high-performance sport practitioners who work in dynamic environments. Two of the notions explored in this thesis were: how a single analytical approach can be applied to multiple problems and, alternatively, how multiple analytical approaches can be applied to a single problem. To address the former, the two machine learning algorithms most prevalent in this thesis were rule association and decision trees, which in Chapters Four and Five, were applied to summarise a large quantity of constraint interactions across a range of activities. While in Chapter Seven, these same techniques were applied to evaluate the influence of a single constraint manipulation within one activity. Taken together, these chapters demonstrate the flexibility of the same analytical techniques to address various questions related to practice design. Alternatively, the rule association and decision tree analysis were also applied to evaluate the same activity in Chapter Seven. In this study, the rule association approach provided a simplified output of discretised constraint associations, whereas the classification tree could provide specific values of interest. Similarly, Chapter Six applied both a univariate and multivariate change point analysis to determine an activity's duration, suggesting advantages and disadvantages to each approach. Chapters Six and Seven, therefore, demonstrate the benefits of performing multiple analyses to address a single query in different ways. This allows practitioners to view the same problem through multiple lenses which may help them gain new insights (Browne et al., 2022).

Furthermore, Chapters Six and Seven show the versatility of these techniques to query mixed data types, including discrete and continuous, which are often collected via various sports data sources, such as event logs or player tracking devices. The flexibility of these techniques may allow individualised solutions to be uncovered for coaches in the field, enhancing their ease of interpretation and the potential for findings to be implemented.

8.2 Future directions

This thesis has presented multiple avenues for future research. While this thesis provided tools useful for evaluating player behaviour during training, it did not examine any potential learning outcomes resulting from improved training design. There is scope to investigate how the tools within this thesis may improve the skill acquisition of athletes and their transfer to performance settings. To achieve this, a research design using randomised control trials could be conducted however, the feasibility of such a study is reduced in applied environments such as high-performance sport. Consequentially, it is suggested that future work be directed to examining match data, where possible, to more appropriately evaluate player performance within match conditions (Browne, Sweeting, et al., 2019). For example, the relationship between constraints on kicking in training and the match performance of kicking under similar constraints could be explored to determine the extent to which training has influenced kicking performance. This would alleviate potential disruptions to high performance programs while providing insight into learning outcomes from training.

The tools within this thesis may also be applied to inform the longitudinal structure and design of training, such as within a periodised framework (Farrow & Robertson, 2017; Otte et al., 2019). However, the long-term learning effects of skill acquisition programs remain largely unexplored in high performance sport. The tools within this thesis may be adapted to measure fluctuation in the constraints on skilled behaviour over time (e.g. weeks and months) and their relationship with skill learning. Studies of this nature would build upon the current work by supporting sport practitioners in their design of longitudinal training plans. This would also have broader impacts in high performance sport to guide an organisation's long term player development strategies, such as from youth academy systems through to the professional first team.

The analytical techniques demonstrated in this thesis may be enhanced as the quality and quantity of constraints further improves in the sport training landscape. For example, while Chapter Three explored how the physical location of players on a field may be utilised to measure the constraint of pressure on a continuous scale, future research could use this data to capture information pertaining to player velocity or orientation, which would provide deeper insights into player pressure qualities (G. Andrienko et al., 2017; N. Andrienko & Andrienko, 2013; Link et al., 2016). Moreover, as technology becomes further integrated in high performance sport, there is ongoing opportunity to increase the quantity and sensitivity of constraints collected. For example, inertial measurement sensors may be used to automatically detect kicks and kick types during AF (Cust et al., 2021). As computer vision increases in AF this could be used to automatically collect constraints such as field dimensions or the quantity of players within a training activity. Automating these processes would allow current resources to be re-allocated to other data collection or more detailed analyses. For example, more individual constraints, such as emotional state, or task constraints including coach instruction and feedback could be included in analytical models to provide more detailed insights on how athlete behaviour is shaped during training. As this occurs, more accurate models may be developed capable of predicting player behaviour on unseen data, such as new constraint manipulations. This would support coaches to create new training activity designs with a greater confidence in expected outcomes. To this end, the analytical techniques demonstrated in this thesis provide a suitable methodological platform for future work.

There is further scope to improve collaboration between high-performance staff with the inclusion of new metrics, utilising additional physical movement measures such as accelerations or change of directions (Sheehan, Tribolet, Spurrs, et al., 2020), or other measures of team coordination such as entropy or team separateness (Silva, Vilar, et al., 2016). This data is valuable to provide additional contextual information when evaluating player and team performance. A further advancement in analytical technique application may seek to harness "live" information feedback. For example, the application of a retrospective change point analysis in Chapter Six, or the constraint evaluation in Chapter Seven, may be improved with a progression towards "on-line" analysis. Real time information feedback could be provided to coaches which signal when athlete behaviour drifts from the training objective. This could facilitate in-session training modifications, such as constraint manipulations or activity end times to support athlete learning and improve the efficiency of training time. Such advancements would enhance the current training design methods which are currently limited to pre-determined prescriptions.

8.3 Conclusions

The specific conclusions of this thesis are:

1. Multivariate data analysis is useful to assist coaches to understand constraint interaction and evaluate the efficacy of their training design.
2. A continuous pressure measurement was positively associated with skill efficiency which contrasted with a discrete pressure measurement.
3. The application of a rule association analysis identified important constraint interactions which influenced pressure and possession time for players during training activities.
4. The application of a regression tree analysis determined that individual players adapted similarly between activity types, with one exception during handball only activities where match experienced positively influenced disposal frequency.
5. Univariate and multivariate change point analysis were useful to inform activity duration by determining time points when player behaviour meaningfully altered.
6. Rule association and classification trees determined interactions between technical, tactical and physical player behaviour within a team numerical advantage and disadvantage constraint manipulation.

REFERENCES

Abdollahipour, R., Wulf, G., Psotta, R., & Palomo Nieto, M. (2015). Performance of gymnastics skill benefits from an external focus of attention. *Journal of Sports Sciences, 33*(17), 1807–1813. https://doi.org/10.1080/02640414.2015.1012102

Abernethy, B. (1996). Training the visual-perceptual skills of athletes: Insights from the study of motor expertise. *The American Journal of Sports Medicine*, *24*(6), 89–92.

Abrantes, C. I., Nunes, M. I., MacXãs, V. M., Leite, N. M., & Sampaio, J. E. (2012). Effects of the number of players and game type constraints on heart rate, rating of perceived exertion, and technical actions of small-sided soccer games. *Journal of Strength and Conditioning Research*, *26*(4), 976–981. Scopus. https://doi.org/10.1519/JSC.0b013e31822dd398

Adams, J. A. (1971). A Closed-Loop Theory of Motor Learning. *Journal of Motor Behavior*, *3*(2), 111–150. https://doi.org/10.1080/00222895.1971.10734898

Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data*, 207–216. https://doi.org/10.1145/170035.170072

Agrawal, R., Mannila, H., Srikant, R., Toivonen, H., & Verkamo, A. I. (1996). Fast discovery of association rules. *Advances in Knowledge Discovery and Data Mining*, *12*(1), 307–328.

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. *Proc. 20th Int. Conf. Very Large Data Bases, VLDB*, *1215*, 487–499.

Aguiar, M., Gonçalves, B., Botelho, G., Lemmink, K., & Sampaio, J. (2015). Footballers' movement behaviour during 2-, 3-, 4- and 5-a-side small-sided games. *Journal of Sports Sciences, 33*(12), 1259–1266. https://doi.org/10.1080/02640414.2015.1022571

Alexander, J. P., Bedin, T., Jackson, K. B., & Robertson, S. (2021). Team numerical advantage in Australian rules football: A missing piece of the scoring puzzle? *PLOS ONE*, *16*(7), e0254591. https://doi.org/10.1371/journal.pone.0254591

Alexander, J. P., Spencer, B., Mara, J. K., & Robertson, S. (2019). Collective team behaviour of Australian Rules football during phases of match play. *Journal of Sports Sciences*, *37*(3), 237–243. https://doi.org/10.1080/02640414.2018.1491113

Alexander, J. P., Spencer, B., Sweeting, A. J., Mara, J. K., & Robertson, S. (2019). The influence of match phase and field position on collective team behaviour in Australian Rules football. *Journal of Sports Sciences*, *37*(15), 1699–1707. https://doi.org/10.1080/02640414.2019.1586077

Allen, T., Wilson, S., Cohen, D. D., & Taberner, M. (2021). Drill design using the 'control-chaos continuum': Blending science and art during return to sport following knee injury in elite football. *Physical Therapy in Sport*, *50*, 22–35. https://doi.org/10.1016/j.ptsp.2021.02.011

Almeida, C. H., Duarte, R., Volossovitch, A., & Ferreira, A. P. (2016). Scoring mode and age-related effects on youth soccer teams' defensive performance during small-sided games. *Journal of Sports Sciences*, *34*(14), 1355–1362. https://doi.org/10.1080/02640414.2016.1150602

Altaf, W., Shahbaz, M., & Guergachi, A. (2017). Applications of association rule mining in health informatics: A survey. *Artificial Intelligence Review*, *47*(3), 313–340.

Aminikhanghahi, S., & Cook, D. J. (2017). A survey of methods for time series change point detection. *Knowledge and Information Systems*, *51*(2), 339–367. https://doi.org/10.1007/s10115-016-0987-z

Andrienko, G., Andrienko, N., Budziak, G., Dykes, J., Fuchs, G., von Landesberger, T., & Weber, H. (2017). Visual analysis of pressure in football. *Data Mining and Knowledge Discovery*, *31*(6), 1793–1839. https://doi.org/10.1007/s10618-017-0513-2

Andrienko, N., & Andrienko, G. (2013). Visual analytics of movement: An overview of methods, tools and procedures. *Information Visualization*, *12*(1), 3–24. https://doi.org/10.1177/1473871612457601

Araujo, D., & Davids, K. (2011). What Exactly is Acquired During Skill Acquisition? *Journal of Conciousness Studies*, *18*(3–4), 7–23.

Araújo, D., & Davids, K. (2016). Team Synergies in Sport: Theory and Measures. *Frontiers in Psychology*, *7,* 1449. https://doi.org/10.3389/fpsyg.2016.01449

Araujo, D., Davids, K., Chow, J. Y., Passos, P., & Raab, M. (2009). The development of decision making skill in sport: An ecological dynamics perspective. In D. Araujo & H. Ripoll (Eds.), *Perspectives on Cognition and Action in Sport* (pp. 157–169). Nova Science Publishers, Inc. https://www.novapublishers.com/catalog/product_info.php?products_id=8742

Araújo, D., Davids, K., & Hristovski, R. (2006). The ecological dynamics of decision making in sport. *Psychology of Sport and Exercise*, *7*(6), 653–676. https://doi.org/10.1016/j.psychsport.2006.07.002

Araújo, D., Davids, K., & Passos, P. (2007). Ecological Validity, Representative Design, and Correspondence Between Experimental Task Constraints and Behavioral Setting: Comment on. *Ecological Psychology*, *19*(1), 69–78. https://doi.org/10.1080/10407410709336951

Araújo, D., Hristovski, R., Seifert, L., Carvalho, J., & Davids, K. (2019). Ecological cognition: Expert decision-making behaviour in sport. *International Review of Sport and Exercise Psychology*, *12*(1), 1–25. https://doi.org/10.1080/1750984X.2017.1349826

Aughey, R. J. (2010). Australian Football Player Work Rate: Evidence of Fatigue and Pacing? *International Journal of Sports Physiology and Performance*, *5*(3), 394–405. https://doi.org/10.1123/ijspp.5.3.394

Australian Football League. (2021a). *2021 AFL Annual Report* [Annual Report]. https://resources.afl.com.au/afl/document/2022/03/10/76a16be1-6439-4020-af33-

1cac86639f7e/2021-AFL-Annual-Report.pdf?_ga=2.130622412.252968313.1648181475-820647460.1647339803

Australian Football League. (2021b). *2021 Laws of the Game*. https://resources.afl.com.au/afl/document/2021/05/17/8ee25f9e-5aff-4813-9c5d-1addfa655470/2021-Laws-of-the-Game-.pdf?_ga=2.173672032.252968313.1648181475-820647460.1647339803

Baker, J., Cote, J., & Abernethy, B. (2003). Sport-Specific Practice and the Development of Expert Decision-Making in Team Ball Sports. *Journal of Applied Sport Psychology*, *15*(1), 12–25. https://doi.org/10.1080/10413200305400

Baker, J., Horton, S., Robertson-Wilson, J., & Wall, M. (2003). Nurturing Sport Expertise: Factors Influencing the Development of Elite Athlete. *Journal of Sports Science & Medicine*, *2*(1), 1–9.

Balagué, N., Pol, R., Torrents, C., Ric, A., & Hristovski, R. (2019). On the Relatedness and Nestedness of Constraints. *Sports Medicine - Open*, *5*(1), 6. https://doi.org/10.1186/s40798-019-0178-z

Balague, N., Torrents, C., Hristovski, R., Davids, K., & Araújo, D. (2013). Overview of complex systems in sport. *Journal of Systems Science and Complexity*, *26*(1), 4–13. https://doi.org/10.1007/s11424-013-2285-0

Bardwell, L., Eckley, I., Fearnhead, P., & Grose, D. (2020). *changepoint.mv: Changepoint Analysis for Multivariate Time Series* (1.0.2). https://CRAN.R-project.org/package=changepoint.mv

Bardwell, L., Fearnhead, P., Eckley, I. A., Smith, S., & Spott, M. (2019). Most Recent Changepoint Detection in Panel Data. *Technometrics*, *61*(1), 88–98. https://doi.org/10.1080/00401706.2018.1438926

Barris, S., & Button, C. (2008). A Review of Vision-Based Motion Analysis in Sport. *Sports Medicine*, *38*(12), 1025–1043. https://doi.org/10.2165/00007256-200838120-00006

Bartlett, R. (2001). Performance analysis: Can bringing together biomechanics and notational analysis benefit coaches? *International Journal of Performance Analysis in Sport*, *1*(1), 122–126. https://doi.org/10.1080/24748668.2001.11868254

Baumeister, R. F., & Showers, C. J. (1986). A review of paradoxical performance effects: Choking under pressure in sports and mental tests. *European Journal of Social Psychology*, *16*(4), 361–383. https://doi.org/10.1002/ejsp.2420160405

Bergmann, F., Gray, R., Wachsmuth, S., & Höner, O. (2021). Perceptual-Motor and Perceptual-Cognitive Skill Acquisition in Soccer: A Systematic Review on the Influence of Practice Design and Coaching Behavior. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.772201

Bernstein, N. (1984). Some Emergent Problems of the Regulation of Motor Acts. *Advances in Psychology*, *17*(C), 343–371. Scopus. https://doi.org/10.1016/S0166-4115(08)61376-X

Bishop, D. (2008). An Applied Research Model for the Sport Sciences. *Sports Medicine*, *38*(3), 253–263. https://doi.org/10.2165/00007256-200838030-00005

Black, G. M., Gabbett, T. J., Johnston, R. D., Cole, M. H., Naughton, G., & Dawson, B. (2019). A skill profile of the national women's Australian football league (AFLW). *Science and Medicine in Football*, *3*(2), 138–142. https://doi.org/10.1080/24733938.2018.1489140

Black, G. M., Gabbett, T. J., Naughton, G. A., & McLean, B. D. (2016). The effect of intense exercise periods on physical and technical performance during elite Australian Football match-play: A comparison of experienced and less experienced players. *Journal of Science and Medicine in Sport*, *19*(7), 596–602. https://doi.org/10.1016/j.jsams.2015.07.007

Black, G. M., Gabbett, T. J., Naughton, G., Cole, M. H., Johnston, R. D., & Dawson, B. (2019). The Influence of Contextual Factors on Running Performance in Female Australian Football

Match-Play. *The Journal of Strength & Conditioning Research*, *33*(9), 2488–2495. https://doi.org/10.1519/JSC.0000000000002142

Bonnard, M., Sirin, A. V., Oddsson, L., & Thorstensson, A. (1994). Different strategies to compensate for the effects of fatigue revealed by neuromuscular adaptation processes in humans. *Neuroscience Letters*, *166*(1), 101–105. https://doi.org/10.1016/0304-3940(94)90850-8

Bonney, N., Ball, K., Berry, J., & Larkin, P. (2020). Effects of manipulating player numbers on technical and physical performances participating in an Australian football small-sided game. *Journal of Sports Sciences*, *30*(21), 2430–2436.

Bootsma, R. J. (1989). Accuracy of Perceptual Processes Subserving Different Perception–Action Systems. *The Quarterly Journal of Experimental Psychology Section A*, *41*(3), 489–500. https://doi.org/10.1080/14640748908402378

Borresen, J., & Lambert, M. I. (2008). Quantifying Training Load: A Comparison of Subjective and Objective Methods. *International Journal of Sports Physiology and Performance*, *3*(1), 16–30. https://doi.org/10.1123/ijspp.3.1.16

Borrie, A., Jonsson, G. K., & Magnusson, M. S. (2002). Temporal pattern analysis and its applicability in sport: An explanation and exemplar data. *Journal of Sports Sciences*, *20*(10), 845–852. https://doi.org/10.1080/026404102320675675

Bourbousson, J., Deschamps, T., & Travassos, B. (2014). From Players to Teams: Towards a Multi-Level Approach of Game Constraints in Team Sports. *International Journal of Sports Science & Coaching*, *9*(6), 1393–1406. https://doi.org/10.1260/1747-9541.9.6.1393

Bourbousson, J., Sève, C., & McGarry, T. (2010). Space–time coordination dynamics in basketball: Part 2. The interaction between the two teams. *Journal of Sports Sciences*, *28*(3), 349–358. https://doi.org/10.1080/02640410903503640

Brito, Â., Roriz, P., Silva, P., Duarte, R., & Garganta, J. (2017). Effects of pitch surface and playing position on external load activity profiles and technical demands of young soccer players in match play. *International Journal of Performance Analysis in Sport*, *17*(6), 902–918. https://doi.org/10.1080/24748668.2017.1407207

Broadbent, D. P., Causer, J., Williams, A. M., & Ford, P. R. (2015). Perceptual-cognitive skill training and its transfer to expert performance in the field: Future research directions. *European Journal of Sport Science*, *15*(4), 322–331. https://doi.org/10.1080/17461391.2014.957727

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.

Browne, P., 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*, *66*, 621–630. https://doi.org/10.1016/j.humov.2019.06.013

Browne, P., Sweeting, A. J., & Robertson, S. (2022). Modelling the Influence of Task Constraints on Goal Kicking Performance in Australian Rules Football. *Sports Medicine - Open*, *8*(1), 13. https://doi.org/10.1186/s40798-021-00393-9

Browne, P., Sweeting, A. J., Woods, C. T., & Robertson, S. (2021). Methodological Considerations for Furthering the Understanding of Constraints in Applied Sports. *Sports Medicine - Open*, *7*(1), 22. https://doi.org/10.1186/s40798-021-00313-x

Browne, P., Woods, C. T., Sweeting, A. J., & Robertson, S. (2020). Applications of a working framework for the measurement of representative learning design in Australian football. *PLOS ONE*, *15*(11), e0242336. https://doi.org/10.1371/journal.pone.0242336

Brunswik, E. (1947). *Systematic and representative design of psychological experiments; with results in physical and social perception* (pp. vi, 60). U. of California Press.

Brunswik, E. (1956). *Perception and the Representative Design of Psychological Experiments*. University of California Press.

Buchheit, M., Allen, A., Poon, T. K., Modonutti, M., Gregson, W., & Di Salvo, V. (2014). Integrating different tracking systems in football: Multiple camera semi-automatic system, local position measurement and GPS technologies. *Journal of Sports Sciences*, *32*(20), 1844–1857. https://doi.org/10.1080/02640414.2014.942687

Buchheit, M., & Simpson, B. M. (2017). Player-Tracking Technology: Half-Full or Half-Empty Glass? *International Journal of Sports Physiology and Performance*, *12*(s2), S2-41. https://doi.org/10.1123/ijspp.2016-0499

Burgess, D. J. (2017). The Research Doesn't Always Apply: Practical Solutions to Evidence-Based Training-Load Monitoring in Elite Team Sports. *International Journal of Sports Physiology and Performance*, *12*(s2), S2-S2-141. https://doi.org/10.1123/ijspp.2016-0608

Buszard, T., Reid, M., Masters, R., & Farrow, D. (2016). Scaling the Equipment and Play Area in Children's Sport to improve Motor Skill Acquisition: A Systematic Review. *Sports Medicine*, *46*(6), 829–843. https://doi.org/10.1007/s40279-015-0452-2

Carey, D. L., Ong, K., Whiteley, R., Crossley, K. M., Crow, J., & Morris, M. E. (2018). Predictive Modelling of Training Loads and Injury in Australian Football. *International Journal of Computer Science in Sport*, *17*(1), 49–66. https://doi.org/10.2478/ijcss-2018-0002

Carling, C., & Dupont, G. (2011). Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *Journal of Sports Sciences*, *29*(1), 63–71. https://doi.org/10.1080/02640414.2010.521945

Casamichana, D., & Castellano, J. (2010). Time–motion, heart rate, perceptual and motor behaviour demands in small-sides soccer games: Effects of pitch size. *Journal of Sports Sciences*, *28*(14), 1615–1623. https://doi.org/10.1080/02640414.2010.521168

Castellano, J., Alvarez-Pastor, D., & Bradley, P. S. (2014). Evaluation of Research Using Computerised Tracking Systems (Amisco® and Prozone®) to Analyse Physical Performance in

Elite Soccer: A Systematic Review. *Sports Medicine*, *44*(5), 701–712. https://doi.org/10.1007/s40279-014-0144-3

Chambers, R. M., Gabbett, T. J., Gupta, R., Josman, C., Bown, R., Stridgeon, P., & Cole, M. H. (2019). Automatic detection of one-on-one tackles and ruck events using microtechnology in rugby union. *Journal of Science and Medicine in Sport*, *22*(7), 827–832. https://doi.org/10.1016/j.jsams.2019.01.001

Chandler, P. T., Pinder, S. J., Curran, J. D., & Gabbett, T. J. (2014). Physical Demands of Training and Competition in Collegiate Netball Players. *The Journal of Strength & Conditioning Research*, *28*(10), 2732–2737. https://doi.org/10.1519/JSC.0000000000000486

Charness, N., Tuffiash, M., Krampe, R., Reingold, E., & Vasyukova, E. (2005). The role of deliberate practice in chess expertise. *Applied Cognitive Psychology*, *19*(2), 151–165. https://doi.org/10.1002/acp.1106

Chow, J. Y. (2013). Nonlinear Learning Underpinning Pedagogy: Evidence, Challenges, and Implications. *Quest*, *65*(4), 469–484. https://doi.org/10.1080/00336297.2013.807746

Chow, J. Y., Davids, K., Button, C., & Koh, M. (2007). Variation in Coordination of a Discrete Multiarticular Action as a Function of Skill Level. *Journal of Motor Behavior*, *39*(6), 463–479. https://doi.org/10.3200/JMBR.39.6.463-480

Chow, J. Y., Davids, K., Button, C., & Koh, M. (2008). Coordination changes in a discrete multi-articular action as a function of practice. *Acta Psychologica*, *127*(1), 163–176. https://doi.org/10.1016/j.actpsy.2007.04.002

Chow, J. Y., Davids, K., Hristovski, R., Araújo, D., & Passos, P. (2011). Nonlinear pedagogy: Learning design for self-organizing neurobiological systems. *New Ideas in Psychology*, *29*(2), 189–200. https://doi.org/10.1016/j.newideapsych.2010.10.001

Clark, J. E. (1995). On Becoming Skillful: Patterns and Constraints. *Research Quarterly for Exercise and Sport*, *66*(3), 173–183. https://doi.org/10.1080/02701367.1995.10608831

Clarke, A. C., Ryan, S., Couvalias, G., Dascombe, B. J., Coutts, A. J., & Kempton, T. (2018). Physical demands and technical performance in Australian Football League Women's (AFLW) competition match-play. *Journal of Science and Medicine in Sport*, *21*(7), 748–752. https://doi.org/10.1016/j.jsams.2017.11.018

Clarke, A. C., Whitaker, M., & Sullivan, C. (2021). Evolving peak period, match movement, and performance demands in elite women's Australian football. *Journal of Science and Medicine in Sport*, *24*(7), 683–688. https://doi.org/10.1016/j.jsams.2021.01.006

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., & Martins, F. M. L. (2013). An Online Tactical Metrics Applied to Football Game. *Research Journal of Applied Sciences, Engineering and Technology*, *5*(5), Article 5. https://doi.org/10.19026/rjaset.5.4926

Clemente, F. M., Couceiro, S. M., Martins, F. M. L., Mendes, R., & Figueiredo, A. J. (2013). Measuring Collective Behaviour in Football Teams: Inspecting the impact of each half of the match on ball possession. *International Journal of Performance Analysis in Sport*, *13*(3), 678–689. https://doi.org/10.1080/24748668.2013.11868680

Clemente, F. M., Martins, F. M. L., Mendes, R. S., Couceiro, M. S., & Figueiredo, A. J. (2014). Using collective metrics to inspect spatio-temporal relationships between football players. *South African Journal for Research in Sport, Physical Education and Recreation*, *36*(2), 47–59. https://doi.org/10.10520/EJC159570

Corbett, D. M., Bartlett, J. D., O'connor, F., Back, N., Torres-Ronda, L., & Robertson, S. (2018). Development of physical and skill training drill prescription systems for elite Australian Rules football. *Science and Medicine in Football*, *2*(1), 51–57. https://doi.org/10.1080/24733938.2017.1381344

Corbett, D. M., Sweeting, A. J., & Robertson, S. (2017). Weak Relationships between Stint Duration, Physical and Skilled Match Performance in Australian Football. *Frontiers in Physiology*, *8*. https://doi.org/10.3389/fphys.2017.00820

Corbett, D. M., Sweeting, A. J., & Robertson, S. (2019). A change point approach to analysing the match activity profiles of team-sport athletes. *Journal of Sports Sciences*, *37*(14), 1600–1608. https://doi.org/10.1080/02640414.2019.1577941

Cordovil, R., Araújo, D., Davids, K., Gouveia, L., Barreiros, J., Fernandes, O., & Serpa, S. (2009). The influence of instructions and body-scaling as constraints on decision-making processes in team sports. *European Journal of Sport Science*, *9*(3), 169–179. https://doi.org/10.1080/17461390902763417

Correia, V., Araújo, D., Duarte, R., Travassos, B., Passos, P., & Davids, K. (2012). Changes in practice task constraints shape decision-making behaviours of team games players. *Journal of Science and Medicine in Sport*, *15*(3), 244–249. https://doi.org/10.1016/j.jsams.2011.10.004

Correia, V., Carvalho, J., Araújo, D., Pereira, E., & Davids, K. (2019). Principles of nonlinear pedagogy in sport practice. *Physical Education and Sport Pedagogy*, *24*(2), 117–132. https://doi.org/10.1080/17408989.2018.1552673

Côté, J. (1999). The Influence of the Family in the Development of Talent in Sport. *The Sport Psychologist*, *13*(4), 395–417. https://doi.org/10.1123/tsp.13.4.395

Côté, J., Baker, J., & Abernethy, B. (2007). Practice and play in the development of sport expertise. *Handbook of Sport Psychology*, *3*, 184–202.

Cryer, J. D., & Chan, K.-S. (2008). *Time series analysis: With applications in R* (Vol. 2). Springer.

Csataljay, G., James, N., Hughes, M., & Dancs, H. (2013). Effects of defensive pressure on basketball shooting performance. *International Journal of Performance Analysis in Sport*, *13*(3), 594–601. https://doi.org/10.1080/24748668.2013.11868673

Cushion, C. (2007). Modelling the Complexity of the Coaching Process. *International Journal of Sports Science & Coaching*, *2*(4), 427–433.

Cushion, C., Ford, P. R., & Williams, A. M. (2012). Coach behaviours and practice structures in youth soccer: Implications for talent development. *Journal of Sports Sciences*, *30*(15), 1631–1641. https://doi.org/10.1080/02640414.2012.721930

Cust, E. E., Sweeting, A. J., Ball, K., Anderson, H., & Robertson, S. (2019). The relationship of team and individual athlete performances on match quarter outcome in elite women's Australian Rules football. *Journal of Science and Medicine in Sport*, *22*(10), 1157–1162. https://doi.org/10.1016/j.jsams.2019.05.004

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2019). Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance. *Journal of Sports Sciences*, *37*(5), 568–600. https://doi.org/10.1080/02640414.2018.1521769

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2021). Classification of Australian football kick types in-situation via ankle-mounted inertial measurement units. *Journal of Sports Sciences*, *39*(12), 1330–1338. https://doi.org/10.1080/02640414.2020.1868678

Davids, K. (2000). Skill acquisition and the theory of deliberate practice: It ain't what you do it's the way that you do it! *International Journal of Sport Psychology*, *31*(4), 461–466.

Davids, K. (2012). Learning design for Nonlinear Dynamical Movement Systems. *The Open Sports Sciences Journal*, *5*(1). https://benthamopen.com/ABSTRACT/TOSSJ-5-9

Davids, K. (2014). Athletes and sports teams as complex adaptive system: A review of implications for learning design. *RICYDE. Revista Internacional de Ciencias Del Deporte. Doi:10.5232/Ricyde*, *11*(39), Article 39.

Davids, K., & Araújo, D. (2010a). Perception of Affordances in Multi-Scale Dynamics as an Alternative Explanation for Equivalence of Analogical and Inferential Reasoning in Animals and Humans. *Theory & Psychology*, *20*(1), 125–134. https://doi.org/10.1177/0959354309345637

Davids, K., & Araújo, D. (2010b). The concept of 'Organismic Asymmetry' in sport science. *Journal of Science and Medicine in Sport*, *13*(6), 633–640. https://doi.org/10.1016/j.jsams.2010.05.002

Davids, K., Araújo, D., Correia, V., & Vilar, L. (2013). How Small-Sided and Conditioned Games Enhance Acquisition of Movement and Decision-Making Skills. *Exercise and Sport Sciences Reviews*, *41*(3), 154. https://doi.org/10.1097/JES.0b013e318292f3ec

Davids, K., Araújo, D., Shuttleworth, R., & Button, C. (2003). Acquiring skill in sport: A constraints-led perspective. *International Journal of Computer Science in Sport*, *2*(2), 31–39.

Davids, K., Button, C., Araújo, D., Renshaw, I., & Hristovski, R. (2006). Movement Models from Sports Provide Representative Task Constraints for Studying Adaptive Behavior in Human Movement Systems. *Adaptive Behavior*, *14*(1), 73–95. https://doi.org/10.1177/105971230601400103

Davids, K., Button, C., & Bennett, S. J. (2008). *Dynamics of skill acquisition: A constraints-led approach*. Human Kinetics. http://www.humankinetics.com/products/showproduct.cfm?isbn=9780736036863

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement systems as dynamical systems: The functional role of variability and its implications for sports medicine. *Sports Medicine (Auckland, N.Z.)*, *33*(4), 245–260. https://doi.org/10.2165/00007256-200333040-00001

Davids, K., Handford, C., & Williams, M. (1994). The natural physical alternative to cognitive theories of motor behaviour: An invitation for interdisciplinary research in sports science? *Journal of Sports Sciences*, *12*(6), 495–528. https://doi.org/10.1080/02640419408732202

Davids, K., Lees, A., & Burwitz, L. (2000). Understanding and measuring coordination and control in kicking skills in soccer: Implications for talent identification and skill acquisition. *Journal of Sports Sciences*, *18*(9), 703–714. https://doi.org/10.1080/02640410050120087

Dawson, B., Hopkinson, R., Appleby, B., Stewart, G., & Roberts, C. (2004a). Comparison of training activities and game demands in the Australian Football League. *Journal of Science and Medicine in Sport*, *7*(3), 292–301. https://doi.org/10.1016/S1440-2440(04)80024-0

Dawson, B., Hopkinson, R., Appleby, B., Stewart, G., & Roberts, C. (2004b). Player movement patterns and game activities in the Australian Football League. *Journal of Science and Medicine in Sport*, *7*(3), 278–291. https://doi.org/10.1016/S1440-2440(04)80023-9

De'ath, G., & Fabricius, K. E. (2000). Classification and Regression Trees: A Powerful yet Simple Technique for Ecological Data Analysis. *Ecology*, *81*(11), 3178–3192. https://doi.org/10.1890/0012-9658(2000)081[3178:CARTAP]2.0.CO;2

DeKeyser, R., VanPatten, B., & Williams, J. (2007). Skill acquisition theory. *Theories in Second Language Acquisition: An Introduction*, *97113*, 94–112.

Delaney, J. A., Duthie, G. M., Thornton, H. R., Scott, T. J., Gay, D., & Dascombe, B. J. (2016). Acceleration-Based Running Intensities of Professional Rugby League Match Play. *International Journal of Sports Physiology and Performance*, *11*(6), 802–809. https://doi.org/10.1123/ijspp.2015-0424

Delaney, J. A., Scott, T. J., Thornton, H. R., Bennett, K. J. M., Gay, D., Duthie, G. M., & Dascombe, B. J. (2015). Establishing Duration-Specific Running Intensities From Match-Play Analysis in Rugby League. *International Journal of Sports Physiology and Performance*, *10*(6), 725–731. https://doi.org/10.1123/ijspp.2015-0092

Delaney, J. A., Thornton, H. R., Burgess, D. J., Dascombe, B. J., & Duthie, G. M. (2017). Duration-specific running intensities of Australian Football match-play. *Journal of Science and Medicine in Sport*, *20*(7), 689–694. https://doi.org/10.1016/j.jsams.2016.11.009

Dorel, S., Drouet, J.-M., Couturier, A., Champoux, Y., & Hug, F. (2009). Changes of pedaling technique and muscle coordination during an exhaustive exercise. *Medicine and Science in Sports and Exercise*, *41*(6), 1277–1286. Scopus. https://doi.org/10.1249/MSS.0b013e31819825f8

Dunwoody, P. T. (2006). The neglect of the environment by cognitive psychology. *Journal of Theoretical and Philosophical Psychology*, *26*(1–2), 139–153. https://doi.org/10.1037/h0091271

Dutt-Mazumder, A., Button, C., Robins, A., & Bartlett, R. (2011). Neural Network Modelling and Dynamical System Theory. *Sports Medicine*, *41*(12), 1003–1017. https://doi.org/10.2165/11593950-000000000-00000

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, *100*(3), 363–406. https://doi.org/10.1037/0033-295X.100.3.363

Ericsson, K. A., & Smith, J. (1991). *Toward a General Theory of Expertise: Prospects and Limits*. Cambridge University Press.

Eysenck, M. W. (2013). *Anxiety: The Cognitive Perspective*. Psychology Press.

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. (2013). Regression Models. In L. Fahrmeir, T. Kneib, S. Lang, & B. Marx (Eds.), *Regression: Models, Methods and Applications* (pp. 21–72). Springer. https://doi.org/10.1007/978-3-642-34333-9_2

Fajen, B. R., Riley, M. A., & Turvey, M. T. (2008). Information, affordances, and the control of action in sport. *International Journal of Sport Psychology*, *40*(1), 79–107.

Farrow, D., Pyne, D., & Gabbett, T. (2008). Skill and Physiological Demands of Open and Closed Training Drills in Australian Football. *International Journal of Sports Science & Coaching*, *3*(4), 489–499. https://doi.org/10.1260/174795408787186512

Farrow, D., & Reid, M. (2010). The effect of equipment scaling on the skill acquisition of beginning tennis players. *Journal of Sports Sciences*, *28*(7), 723–732. https://doi.org/10.1080/02640411003770238

Farrow, D., & Robertson, S. (2017). Development of a Skill Acquisition Periodisation Framework for High-Performance Sport. *Sports Medicine*, *47*(6), 1043–1054. https://doi.org/10.1007/s40279-016-0646-2

Fereday, K., Hills, S. P., Russell, M., Smith, J., Cunningham, D. J., Shearer, D., McNarry, M., & Kilduff, L. P. (2020). A comparison of rolling averages versus discrete time epochs for assessing the worst-case scenario locomotor demands of professional soccer match-play. *Journal of Science and Medicine in Sport*, *23*(8), 764–769. https://doi.org/10.1016/j.jsams.2020.01.002

Fernandez, J., & Bornn, L. (2018). Wide open spaces: A statistical technique for measuring space creation in professional soccer. *Sloan Sports Analytics Conference*, *2018*.

Fitzpatrick, A., Davids, K., & Stone, J. A. (2018). Effects of scaling task constraints on emergent behaviours in children's racquet sports performance. *Human Movement Science*, *58*, 80–87. https://doi.org/10.1016/j.humov.2018.01.007

Fleay, B., Joyce, C., Banyard, H., & Woods, C. (2018). Manipulating Field Dimensions During Small-sided Games Impacts the Technical and Physical Profiles of Australian Footballers. *Journal of Strength and Conditioning Research*, *32*(7), 2039–2044. https://doi.org/10.1519/JSC.0000000000002423

Fonseca, S., Milho, J., Travassos, B., Araújo, D., & Lopes, A. (2013). Measuring spatial interaction behavior in team sports using superimposed Voronoi diagrams. *International Journal of Performance Analysis in Sport*, *13*(1), 179–189. https://doi.org/10.1080/24748668.2013.11868640

Ford, P. R., Yates, I., & Williams, A. M. (2010). An analysis of practice activities and instructional behaviours used by youth soccer coaches during practice: Exploring the link between science and application. *Journal of Sports Sciences*, *28*(5), 483–495. https://doi.org/10.1080/02640410903582750

Fransen, J., Bennett, K. J. M., Woods, C. T., French-Collier, N., Deprez, D., Vaeyens, R., & Lenoir, M. (2017). Modelling age-related changes in motor competence and physical fitness in high-level youth soccer players: Implications for talent identification and development. *Science and Medicine in Football*, *1*(3), 203–208. https://doi.org/10.1080/24733938.2017.1366039

Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of centroid position and surface area of soccer teams in small-sided games. *European Journal of Sport Science*, *11*(4), 215–223. https://doi.org/10.1080/17461391.2010.499967

Frencken, W., Van Der Plaats, J., Visscher, C., & Lemmink, K. (2013). Size matters: Pitch dimensions constrain interactive team behaviour in soccer. *Journal of Systems Science and Complexity*, *26*(1), 85–93. https://doi.org/10.1007/s11424-013-2284-1

Fu, T. (2011). A review on time series data mining. *Engineering Applications of Artificial Intelligence*, *24*(1), 164–181. https://doi.org/10.1016/j.engappai.2010.09.007

Fulton, S. K., Pyne, D. B., & Burkett, B. (2009a). Validity and reliability of kick count and rate in freestyle using inertial sensor technology. *Journal of Sports Sciences*, *27*(10), 1051–1058. https://doi.org/10.1080/02640410902998247

Fulton, S. K., Pyne, D. B., & Burkett, B. (2009b). Quantifying freestyle kick-count and kick-rate patterns in Paralympic swimming. *Journal of Sports Sciences*, *27*(13), 1455–1461. https://doi.org/10.1080/02640410903062936

Gabbett, T. (2006). Skill-based conditioning games as an alternative to traditional conditioning for rugby league players. *The Journal of Strength & Conditioning Research*, *20*(2), 306–315.

Gabbett, T., Jenkins, D., & Abernethy, B. (2009). Game-Based Training for Improving Skill and Physical Fitness in Team Sport Athletes. *International Journal of Sports Science & Coaching*, *4*(2), 273–283. https://doi.org/10.1260/174795409788549553

Ghosalkar, N. N., & Dhage, S. N. (2018). Real Estate Value Prediction Using Linear Regression. *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*, 1–5. https://doi.org/10.1109/ICCUBEA.2018.8697639

Gibson, J. J. (1979). *The Ecological Approach to Visual Perception*. Houghton Mifflin.

Gibson, J. J. (2014). *The Ecological Approach to Visual Perception: Classic Edition*. Psychology Press. https://doi.org/10.4324/9781315740218

Gibson, J. J., & Carmichael, L. (1966). *The senses considered as perceptual systems* (Vol. 2). Houghton Mifflin Boston.

Giles, B., Kovalchik, S., & Reid, M. (2020). A machine learning approach for automatic detection and classification of changes of direction from player tracking data in professional tennis. *Journal of Sports Sciences*, *38*(1), 106–113. https://doi.org/10.1080/02640414.2019.1684132

Glazier, P. S. (2010). Game, Set and Match? Substantive Issues and Future Directions in Performance Analysis. *Sports Medicine*, *40*(8), 625–634. https://doi.org/10.2165/11534970-000000000-00000

Glazier, P. S. (2017). Towards a Grand Unified Theory of sports performance. *Human Movement Science*, *56*, 139–156. https://doi.org/10.1016/j.humov.2015.08.001

Glazier, P. S., & Davids, K. (2009). Constraints on the Complete Optimization of Human Motion. *Sports Medicine*, *39*(1), 15–28. https://doi.org/10.2165/00007256-200939010-00002

Golonka, S., & Wilson, A. D. (2019). Ecological Representations. *Ecological Psychology*, *31*(3), 235–253. https://doi.org/10.1080/10407413.2019.1615224

Gould, D., & Mallett, C. (2020). *Sport Coaches' Handbook*. Human Kinetics.

Gray, A., & Jenkins, D. G. (2010). Match Analysis and the Physiological Demands of Australian Football. *Sports Medicine*, *40*(4), 347–360. https://doi.org/10.2165/11531400-000000000-00000

Gray, R. (2020). Comparing the constraints led approach, differential learning and prescriptive instruction for training opposite-field hitting in baseball. *Psychology of Sport and Exercise*, *51*, 101797. https://doi.org/10.1016/j.psychsport.2020.101797

Greenwood, D., Davids, K., & Renshaw, I. (2012). How Elite Coaches' Experiential Knowledge Might Enhance Empirical Research on Sport Performance. *International Journal of Sports Science & Coaching*, *7*(2), 411–422. https://doi.org/10.1260/1747-9541.7.2.411

Greenwood, D., Davids, K., & Renshaw, I. (2014). Experiential knowledge of expert coaches can help identify informational constraints on performance of dynamic interceptive actions. *Journal of Sports Sciences*, *32*(4), 328–335. https://doi.org/10.1080/02640414.2013.824599

Guadagnoli, M., & Lee, T. D. (2004). Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning. *Journal of Motor Behavior*, *36*(2), 212–224. https://doi.org/10.3200/JMBR.36.2.212-224

Guadagnoli, M., & Lindquist, K. (2007). Challenge Point Framework and Efficient Learning of Golf. *International Journal of Sports Science & Coaching*, *2*(1_suppl), 185–197. https://doi.org/10.1260/174795407789705505

Gudmundsson, J., & Horton, M. (2017). Spatio-Temporal Analysis of Team Sports. *ACM Comput. Surv.*, *50*(2), 22:1-22:34. https://doi.org/10.1145/3054132

Gudmundsson, J., & Wolle, T. (2014). Football analysis using spatio-temporal tools. *Computers, Environment and Urban Systems*, *47*, 16–27. https://doi.org/10.1016/j.compenvurbsys.2013.09.004

Gunst, R. F., & Mason, R. L. (2019). *Regression Analysis and Its Application: A Data-Oriented Approach*. CRC Press. https://doi.org/10.1201/9780203741054

Gupta, A., Nagarajan, V., & Ravi, R. (2017). Approximation Algorithms for Optimal Decision Trees and Adaptive TSP Problems. *Mathematics of Operations Research*, *42*(3), 876–896. https://doi.org/10.1287/moor.2016.0831

Gustin, W. C. (1985). The development of exceptional research mathematicians. *Developing Talent in Young People*, 270–331.

Haff, G. (2010). Quantifying Workloads in Resistance Training: A Brief Review. *Prof. Strength and Cond.*, *10*, 31–40.

Hahsler, M., Grün, B., & Hornik, K. (2005). arules—A Computational Environment for Mining Association Rules and Frequent Item Sets. *Journal of Statistical Software*, *14*, 1–25. https://doi.org/10.18637/jss.v014.i15

Hahsler, M., & Johnson, I. (2020). *ArulesCBA: Classification Based on Association Rules* (R package version 1.2.0). https://CRAN.R-project.org/package=arulesCBA

Handford, C., Davids, K., Bennett, S., & Button, C. (1997). Skill acquisition in sport: Some applications of an evolving practice ecology. *Journal of Sports Sciences*, *15*(6), 621–640. https://doi.org/10.1080/026404197367056

Harvey, A. C., Henry, S. G. B., Peters, S., & Wren-Lewis, S. (1986). Stochastic Trends in Dynamic Regression Models: An Application to the Employment-Output Equation. *The Economic Journal*, *96*(384), 975–985. https://doi.org/10.2307/2233168

Headrick, J., Renshaw, I., Davids, K., Pinder, R. A., & Araújo, D. (2015). The dynamics of expertise acquisition in sport: The role of affective learning design. *Psychology of Sport and Exercise*, *16*, 83–90. https://doi.org/10.1016/j.psychsport.2014.08.006

Helsen, W. F., Starkes, J. L., & Hodges, N. J. (1998). Team Sports and the Theory of Deliberate Practice. *Journal of Sport and Exercise Psychology*, *20*(1), 12–34. https://doi.org/10.1123/jsep.20.1.12

Higham, D. G., Hopkins, W. G., Pyne, D. B., & Anson, J. M. (2014). Performance Indicators Related to Points Scoring and Winning in International Rugby Sevens. *Journal of Sports Science & Medicine*, *13*(2), 358–364.

Hodges, N. J., & Franks, I. M. (2002). Modelling coaching practice: The role of instruction and demonstration. *Journal of Sports Sciences*, *20*(10), 793–811. https://doi.org/10.1080/026404102320675648

Hodges, N. J., & Williams, A. M. (2012). *Skill Acquisition in Sport: Research, Theory and Practice*. Routledge.

Horton, M., Gudmundsson, J., Chawla, S., & Estephan, J. (2015). Automated Classification of Passing in Football. In T. Cao, E.-P. Lim, Z.-H. Zhou, T.-B. Ho, D. Cheung, & H. Motoda (Eds.), *Advances in Knowledge Discovery and Data Mining* (pp. 319–330). Springer International Publishing. https://doi.org/10.1007/978-3-319-18032-8_25

Horvat, T., & Job, J. (2020). The use of machine learning in sport outcome prediction: A review. *WIREs Data Mining and Knowledge Discovery*, *10*(5), e1380. https://doi.org/10.1002/widm.1380

Howe, M. J. A., Davidson, J. W., & Sloboda, J. A. (1998). Innate talents: Reality or myth? *Behavioral and Brain Sciences*, *21*(3), 399–407. https://doi.org/10.1017/S0140525X9800123X

Hughes, M. (2004). Performance analysis – a 2004 perspective. *International Journal of Performance Analysis in Sport*, *4*(1), 103–109. https://doi.org/10.1080/24748668.2004.11868296

Hughes, M., & Bartlett, R. M. (2002). The use of performance indicators in performance analysis. *Journal of Sports Sciences*, *20*(10), 739–754. https://doi.org/10.1080/026404102320675602

Hughes, M., & Franks, I. (2005). Analysis of passing sequences, shots and goals in soccer. *Journal of Sports Sciences*, *23*(5), 509–514. https://doi.org/10.1080/02640410410001716779

I. Schollhorn, W., Hegen, P., & Davids, K. (2012). The Nonlinear Nature of Learning—A Differential Learning Approach [Abstract]. *The Open Sports Sciences Journal*, *5*(1). https://doi.org/10.2174/1875399X01205010100

Impellizzeri, F. M., Marcora, S. M., Castagna, C., Reilly, T., Sassi, A., Iaia, F. M., & Rampinini, E. (2006). Physiological and Performance Effects of Generic versus Specific Aerobic Training in Soccer Players. *International Journal of Sports Medicine*, *27*(6), 483–492. https://doi.org/10.1055/s-2005-865839

Ireland, D., Dawson, B., Peeling, P., Lester, L., Heasman, J., & Rogalski, B. (2019). Do we train how we play? Investigating skill patterns in Australian football. *Science and Medicine in Football*, *3*(4), 265–274. https://doi.org/10.1080/24733938.2019.1595111

Iyer, S. R., & Sharda, R. (2009). Prediction of athletes performance using neural networks: An application in cricket team selection. *Expert Systems with Applications*, *36*(3, Part 1), 5510–5522. https://doi.org/10.1016/j.eswa.2008.06.088

Jacobs, D. M., & Michaels, C. F. (2007). Direct Learning. *Ecological Psychology*, *19*(4), 321–349. https://doi.org/10.1080/10407410701432337

Janelle, C. M., & Hillman, C. H. (2003). Expert performance in sport. In *Expert performance in sports: Advances in research on sport expertise* (pp. 19–47). Human Kinetics.

Johnston, R. D., Black, G. M., Harrison, P. W., Murray, N. B., & Austin, D. J. (2018). Applied Sport Science of Australian Football: A Systematic Review. *Sports Medicine*, *48*(7), 1673–1694. https://doi.org/10.1007/s40279-018-0919-z

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*. Oxford University Press, USA.

Keele, S. W. (1968). Movement control in skilled motor performance. *Psychological Bulletin*, *70*(6, Pt.1), 387–403. https://doi.org/10.1037/h0026739

Kelly, D. M., & Drust, B. (2009). The effect of pitch dimensions on heart rate responses and technical demands of small-sided soccer games in elite players. *Journal of Science and Medicine in Sport*, *12*(4), 475–479. https://doi.org/10.1016/j.jsams.2008.01.010

Kelso, J. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. MIT press.

Killick, R., & Eckley, I. A. (2014). changepoint: An R Package for Changepoint Analysis. *Journal of Statistical Software*, *58*(1), Article 1. https://doi.org/10.18637/jss.v058.i03

Kinnerk, P., Kearney, P. E., Harvey, S., & Lyons, M. (2021). An investigation of high-performance team sport coaches' planning practices. *Sports Coaching Review*. Scopus. https://doi.org/10.1080/21640629.2021.1990653

Komar, J., Potdevin, F., Chollet, D., & Seifert, L. (2019). Between exploitation and exploration of motor behaviours: Unpacking the constraints-led approach to foster nonlinear learning in physical education. *Physical Education and Sport Pedagogy*, *24*(2), 133–145. https://doi.org/10.1080/17408989.2018.1557133

Krampe, R. T. (1994). *Maintaining excellence: Cognitive-motor performance in pianists differing in age and skill level*. Max-Planck-Institut für Bildungsforschung.

Krause, L., Farrow, D., Reid, M., Buszard, T., & Pinder, R. (2018). Helping coaches apply the principles of representative learning design: Validation of a tennis specific practice assessment tool. *Journal of Sports Sciences*, *36*(11), 1277–1286. https://doi.org/10.1080/02640414.2017.1374684

Kugler, P. N., Kelso, J. S., & Turvey, M. T. (1982). On the control and coordination of naturally developing systems. *The Development of Movement Control and Coordination*, *5*, 1–78.

Kugler, P. N., Scott Kelso, J. A., & Turvey, M. T. (1980). On the Concept of Coordinative Structures as Dissipative Structures: I. Theoretical Lines of Convergence. In G. E. Stelmach & J. Requin (Eds.), *Advances in Psychology* (Vol. 1, pp. 3–47). North-Holland. https://doi.org/10.1016/S0166-4115(08)61936-6

Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*, *33*(1), 159–174. JSTOR. https://doi.org/10.2307/2529310

Lane, J. C., Ploeg, G. van der, Greenham, G., & Norton, K. (2020). Characterisation of offensive and defensive game play trends in the Australian Football League (1999–2019). *International Journal of Performance Analysis in Sport*, *20*(4), 557–568. https://doi.org/10.1080/24748668.2020.1758438

Larkin, P., Marchant, D., Syder, A., & Farrow, D. (2020). An eye for talent: The recruiters' role in the Australian Football talent pathway. *PLOS ONE*, *15*(11), e0241307. https://doi.org/10.1371/journal.pone.0241307

Lascu, A., Spratford, W., Pyne, D. B., & Etxebarria, N. (2021). “Train how you play”: Using representative learning design to train amateur cricketers. *Journal of Sports Sciences*, *40*(5), 498–508. https://doi.org/10.1080/02640414.2021.2001160

Lee, T. D., & Genovese, E. D. (2013). Distribution of Practice in Motor Skill Acquisition: Different Effects for Discrete and Continuous Tasks. *Research Quarterly for Exercise and Sport*, *60*(1), 59–65.

Link, D., Lang, S., & Seidenschwarz, P. (2016). Real Time Quantification of Dangerousity in Football Using Spatiotemporal Tracking Data. *PLoS ONE*, *11*(12), e0168768. https://doi.org/10.1371/journal.pone.0168768

Linke, D., Link, D., & Lames, M. (2018). Validation of electronic performance and tracking systems EPTS under field conditions. *PLOS ONE*, *13*(7), e0199519. https://doi.org/10.1371/journal.pone.0199519

Liu, B., Hsu, W., & Ma, Y. (1998). Integrating classification and association rule mining. *Proceedings of the Fourth International Conference on Knowledge Discovery and Data Mining*, 80–86.

Liu, H., Gomez, M.-Á., Lago-Peñas, C., & Sampaio, J. (2015). Match statistics related to winning in the group stage of 2014 Brazil FIFA World Cup. *Journal of Sports Sciences*, *33*(12), 1205–1213. https://doi.org/10.1080/02640414.2015.1022578

Loh, W.-Y. (2011). Classification and regression trees. *WIREs Data Mining and Knowledge Discovery*, *1*(1), 14–23. https://doi.org/10.1002/widm.8

Looney, M. A. (2004). Evaluating judge performance in sport. *Journal of Applied Measurement*, *5*(1), 31–47.

Low, J., Williams, A. M., McRobert, A. P., & Ford, P. R. (2013). The microstructure of practice activities engaged in by elite and recreational youth cricket players. *Journal of Sports Sciences*, *31*(11), 1242–1250. https://doi.org/10.1080/02640414.2013.778419

Lucey, P., Bialkowski, A., Monfort, M., Carr, P., & Matthews, I. (2014). “Quality vs Quantity”: Improved Shot Prediction in Soccer using Strategic Features from Spatiotemporal Data. *Proc. 8th Annual Mit Sloan Sports Analytics Conference*, 1–9.

Lyons, M., Al-Nakeeb, Y., & Nevill, A. (2006). The Impact of Moderate and High Intensity Total Body Fatigue on Passing Accuracy in Expert and Novice Basketball Players. *Journal of Sports Science & Medicine*, *5*(2), 215–227.

Mackenzie, R., & Cushion, C. (2013). Performance analysis in football: A critical review and implications for future research. *Journal of Sports Sciences*, *31*(6), 639–676.

Magill, R., & Anderson, D. (2010). *Motor learning and control*. McGraw-Hill Publishing New York.

Masson, M. E. J. (1990). Cognitive theories of skill acquisition. *Human Movement Science*, *9*(3), 221–239. https://doi.org/10.1016/0167-9457(90)90004-W

McCosker, C., Otte, F., Rothwell, M., & Davids, K. (2021). Principles for technology use in athlete support across the skill level continuum: *International Journal of Sports Science & Coaching*, *17*(2), 437–444. https://doi.org/10.1177/17479541211033471

McCosker, C., Renshaw, I., Greenwood, D., Davids, K., & Gosden, E. (2019). How performance analysis of elite long jumping can inform representative training design through identification of key constraints on competitive behaviours. *European Journal of Sport Science*, *19*(7), 913–921. https://doi.org/10.1080/17461391.2018.1564797

McGarry, T. (2009). Applied and theoretical perspectives of performance analysis in sport: Scientific issues and challenges. *International Journal of Performance Analysis in Sport*, *9*(1), 128–140. https://doi.org/10.1080/24748668.2009.11868469

McIntosh, S., Jackson, K. B., & Robertson, S. (2021). Apples and oranges? Comparing player performances between the Australian Football League and second-tier leagues. *Journal of Sports Sciences*, *39*(18), 2123–2132. https://doi.org/10.1080/02640414.2021.1921372

McIntosh, S., Kovalchik, S., & Robertson, S. (2018a). Examination of player role in the Australian Football League using match performance data. *International Journal of Performance Analysis in Sport*, *18*(3), 451–462. https://doi.org/10.1080/24748668.2018.1486116

McIntosh, S., Kovalchik, S., & Robertson, S. (2018b). Validation of the Australian Football League Player Ratings. *International Journal of Sports Science & Coaching*, *13*(6), 1064–1071. https://doi.org/10.1177/1747954118758000

McIntosh, S., Kovalchik, S., & Robertson, S. (2019). Comparing subjective and objective evaluations of player performance in Australian Rules football. *PLOS ONE*, *14*(8), e0220901. https://doi.org/10.1371/journal.pone.0220901

Metalis, S. A. (1985). Effects of Massed versus Distributed Practice on Acquisition of Video Game Skill. *Perceptual and Motor Skills*, *61*(2), 457–458. https://doi.org/10.2466/pms.1985.61.2.457

Mohammed, M., Khan, M. B., & Bashier, E. B. M. (2016). *Machine learning: Algorithms and applications*. Crc Press.

Mooney, M., O'Brien, B., Cormack, S., Coutts, A., Berry, J., & Young, W. (2011). The relationship between physical capacity and match performance in elite Australian football: A mediation approach. *Journal of Science and Medicine in Sport*, *14*(5), 447–452. https://doi.org/10.1016/j.jsams.2011.03.010

Moreira, A., Bilsborough, J. C., Sullivan, C. J., Cianciosi, M., Aoki, M. S., & Coutts, A. J. (2015). Training Periodization of Professional Australian Football Players During an Entire Australian Football League Season. *International Journal of Sports Physiology and Performance*, *10*(5), 566–571. https://doi.org/10.1123/ijspp.2014-0326

Morgan, S., Williams, M. D., & Barnes, C. (2013). Applying decision tree induction for identification of important attributes in one-versus-one player interactions: A hockey exemplar. *Journal of Sports Sciences*, *31*(10), 1031–1037. https://doi.org/10.1080/02640414.2013.770906

Nash, C. S., & Collins, D. (2006). Tacit Knowledge in Expert Coaching: Science or Art? *Quest*, *58*(4), 465–477. https://doi.org/10.1080/00336297.2006.10491894

Nash, C. S., Sproule, J., & Horton, P. (2011). Excellence in Coaching. *Research Quarterly for Exercise and Sport*, *82*(2), 229–238. https://doi.org/10.1080/02701367.2011.10599750

Newcombe, D. J., Roberts, W. M., Renshaw, I., & Davids, K. (2019). The effectiveness of constraint-led training on skill development in interceptive sports: A systematic review (Clark, McEwan and Christie) – A Commentary. *International Journal of Sports Science & Coaching*, *14*(2), 241–254. https://doi.org/10.1177/1747954119829918

Newell, K. M. (1985). Coordination, Control and Skill. In D. Goodman, R. B. Wilberg, & I. M. Franks (Eds.), *Advances in Psychology* (Vol. 27, pp. 295–317). North-Holland. https://doi.org/10.1016/S0166-4115(08)62541-8

Newell, K. M. (1986). Constraints on the development of coordination. In M. Wade & H. Whiting (Eds.), *Motor Development in children: Aspects of coordination and control* (pp. 341–360). Martinus Nijhoff.

Newell, K. M. (1991). Motor Skill Acquisition. *Annual Review of Psychology*, *42*(1), 213–237. https://doi.org/10.1146/annurev.ps.42.020191.001241

Newell, K. M., & Jordan, K. (2007). Task constraints and movement organization: A common language. In *Ecological task analysis and movement* (pp. 5–23). Human Kinetics.

Newell, K. M., Liu, Y.-T., & Mayer-Kress, G. (2001). Time scales in motor learning and development. *Psychological Review*, *108*(1), 57.

Newell, K. M., & McDonald, P. V. (1992). Searching for solutions to the coordination function: Learning as exploratory behavior. In *Tutorials in motor behavior, 2.* (pp. 517–532). North-Holland.

Newell, K. M., & Rovegno, I. (1990). Commentary—Motor learning: Theory and practice. *Quest*, *42*(2), 184–192.

Nguyen, L. T. T., Vo, B., Hong, T.-P., & Thanh, H. C. (2012). Classification based on association rules: A lattice-based approach. *Expert Systems with Applications*, *39*(13), 11357–11366. https://doi.org/10.1016/j.eswa.2012.03.036

Nunes, N. A., Gonçalves, B., Davids, K., Esteves, P., & Travassos, B. (2021). How manipulation of playing area dimensions in ball possession games constrains physical effort and technical actions in under-11, under-15 and under-23 soccer players. *Research in Sports Medicine*, *29*(2), 170–184. https://doi.org/10.1080/15438627.2020.1770760

O'Brien-Smith, J., Fransen, J., Sheehan, W. B., Lenoir, M., Bennett, K., & Smith, M. R. (2021). Collective behaviour in high and low-level youth soccer. *Science and Medicine in Football*, *6*(2), 164–171. https://doi.org/10.1080/24733938.2021.1917774

O'Connor, D., Larkin, P., Robertson, S., & Goodyear, P. (2022). The art of the question: The structure of questions posed by youth soccer coaches during training. *Physical Education and Sport Pedagogy*, *27*(3), 304–319. https://doi.org/10.1080/17408989.2021.1877270

O'Donoghue, P. (2009). *Research Methods for Sports Performance Analysis*. Routledge. https://doi.org/10.4324/9780203878309

Ofoghi, B., Zeleznikow, J., MacMahon, C., & Raab, M. (2013). Data Mining in Elite Sports: A Review and a Framework. *Measurement in Physical Education and Exercise Science*, *17*(3), 171–186. https://doi.org/10.1080/1091367X.2013.805137

Oliva-Lozano, J. M., Barbier, X., Fortes, V., & Muyor, J. M. (2021). Key load indicators and load variability in professional soccer players: A full season study. *Research in Sports Medicine*, *0*(0), 1–13. https://doi.org/10.1080/15438627.2021.1954517

Ometto, L., Vasconcellos, F. V., Cunha, F. A., Teoldo, I., Souza, C. R. B., Dutra, M. B., O'Sullivan, M., & Davids, K. (2018). How manipulating task constraints in small-sided and conditioned games shapes emergence of individual and collective tactical behaviours in football:

A systematic review. *International Journal of Sports Science & Coaching*, *13*(6), 1200–1214. https://doi.org/10.1177/1747954118769183

Orth, D., Davids, K., Araújo, D., Renshaw, I., & Passos, P. (2014). Effects of a defender on run-up velocity and ball speed when crossing a football. *European Journal of Sport Science*, *14*(sup1), S316–S323. https://doi.org/10.1080/17461391.2012.696712

Orth, D., Davids, K., Chow, J.-Y., Brymer, E., & Seifert, L. (2018). Behavioral Repertoire Influences the Rate and Nature of Learning in Climbing: Implications for Individualized Learning Design in Preparation for Extreme Sports Participation. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00949

Orth, D., Kamp, J. van der, & Button, C. (2019). Learning to be adaptive as a distributed process across the coach–athlete system: Situating the coach in the constraints-led approach. *Physical Education and Sport Pedagogy*, *24*(2), 146–161. https://doi.org/10.1080/17408989.2018.1557132

Orth, D., van der Kamp, J., Memmert, D., & Savelsbergh, G. J. P. (2017). Creative Motor Actions As Emerging from Movement Variability. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.01903

O'Shaughnessy, D. M. (2006). Possession Versus Position: Strategic Evaluation in AFL. *Journal of Sports Science & Medicine*, *5*(4), 533–540.

Osório, A. (2020). Performance Evaluation: Subjectivity, Bias and Judgment Style in Sport. *Group Decision and Negotiation*, *29*(4), 655–678. https://doi.org/10.1007/s10726-020-09672-4

Otte, F. W., Davids, K., Millar, S.-K., & Klatt, S. (2020). When and How to Provide Feedback and Instructions to Athletes?—How Sport Psychology and Pedagogy Insights Can Improve Coaching Interventions to Enhance Self-Regulation in Training. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.01444

Otte, F. W., Millar, S.-K., & Klatt, S. (2019). Skill Training Periodization in “Specialist” Sports Coaching—An Introduction of the “PoST” Framework for Skill Development. *Frontiers in Sports and Active Living*, *1*. https://doi.org/10.3389/fspor.2019.00061

Owen, A. L., Wong, D. P., McKenna, M., & Dellal, A. (2011). Heart Rate Responses and Technical Comparison Between Small- vs. Large-Sided Games in Elite Professional Soccer. *The Journal of Strength & Conditioning Research*, *25*(8), 2104–2110. https://doi.org/10.1519/JSC.0b013e3181f0a8a3

Panteli, F., Smirniotou, A., & Theodorou, A. (2016). Performance environment and nested task constraints influence long jump approach run: A preliminary study. *Journal of Sports Sciences*, *34*(12), 1116–1123. https://doi.org/10.1080/02640414.2015.1092567

Passos, P., Araújo, D., Davids, K., & Shuttleworth, R. (2008). Manipulating Constraints to Train Decision Making in Rugby Union. *International Journal of Sports Science & Coaching*, *3*(1), 125–140. https://doi.org/10.1260/174795408784089432

Passos, P., Cordovil, R., Fernandes, O., & Barreiros, J. (2012). Perceiving affordances in rugby union. *Journal of Sports Sciences*, *30*(11), 1175–1182. https://doi.org/10.1080/02640414.2012.695082

Pill, S. (2014). Informing Game Sense pedagogy with constraints led theory for coaching in Australian football. *Sports Coaching Review*, *3*(1), 46–62. https://doi.org/10.1080/21640629.2014.890778

Pinder, R. A., Davids, K., Renshaw, I., & Araújo, D. (2011). Representative Learning Design and Functionality of Research and Practice in Sport. *Journal of Sport and Exercise Psychology*, *33*(1), 146–155. https://doi.org/10.1123/jsep.33.1.146

Pinder, R. A., Renshaw, I., & Davids, K. (2009). Information–movement coupling in developing cricketers under changing ecological practice constraints. *Human Movement Science*, *28*(4), 468–479. https://doi.org/10.1016/j.humov.2009.02.003

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? Investigating effects of interacting constraints on place kicking performance at the 2015 Rugby Union World Cup. *European Journal of Sport Science*, *18*(10), 1309–1316. https://doi.org/10.1080/17461391.2018.1486459

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2021). Effects of manipulating specific individual constraints on performance outcomes, emotions, and movement phase durations in Rugby Union place kicking. *Human Movement Science*, *79*, 102848. https://doi.org/10.1016/j.humov.2021.102848

Pocock, C., Bezodis, N. E., Wadey, R., & North, J. S. (2020). Understanding Key Constraints and Practice Design in Rugby Union Place Kicking: Experiential Knowledge of Professional Kickers and Experienced Coaches. *International Journal of Sports Science & Coaching*, *15*(5–6), 631–641.

Pol, R., Balagué, N., Ric, A., Torrents, C., Kiely, J., & Hristovski, R. (2020). Training or Synergizing? Complex Systems Principles Change the Understanding of Sport Processes. *Sports Medicine - Open*, *6*(1), 28. https://doi.org/10.1186/s40798-020-00256-9

Porter, J. M., & Magill, R. A. (2010). Systematically increasing contextual interference is beneficial for learning sport skills. *Journal of Sports Sciences*, *28*(12), 1277–1285. https://doi.org/10.1080/02640414.2010.502946

Power, P., Ruiz, H., Wei, X., & Lucey, P. (2017). Not All Passes Are Created Equal: Objectively Measuring the Risk and Reward of Passes in Soccer from Tracking Data. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1605–1613. https://doi.org/10.1145/3097983.3098051

R Core Team. (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Ranganathan, R., Lee, M.-H., & Newell, K. M. (2020). Repetition Without Repetition: Challenges in Understanding Behavioral Flexibility in Motor Skill. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.02018

Reich, B. J., Hodges, J. S., Carlin, B. P., & Reich, A. M. (2006). A Spatial Analysis of Basketball Shot Chart Data. *The American Statistician*, *60*(1), 3–12. https://doi.org/10.1198/000313006X90305

Rein, R., & Memmert, D. (2016). Big data and tactical analysis in elite soccer: Future challenges and opportunities for sports science. *SpringerPlus*, *5*(1), 1410. https://doi.org/10.1186/s40064-016-3108-2

Rennie, M. J., Kelly, S. J., Bush, S., Spurrs, R. W., Austin, D. J., & Watsford, M. L. (2020). Phases of match-play in professional Australian Football: Distribution of physical and technical performance. *Journal of Sports Sciences*, *38*(14), 1682–1689. https://doi.org/10.1080/02640414.2020.1754726

Rennie, M. J., Watsford, M. L., Spurrs, R. W., Kelly, S. J., & Pine, M. J. (2018). Phases of match-play in professional Australian Football: Descriptive analysis and reliability assessment. *Journal of Science and Medicine in Sport*, *21*(6), 635–639. https://doi.org/10.1016/j.jsams.2017.10.021

Renshaw, I., Araújo, D., Button, C., Chow, J. Y., Davids, K., & Moy, B. (2016). Why the Constraints-Led Approach is not Teaching Games for Understanding: A clarification. *Physical Education and Sport Pedagogy*, *21*(5), 459–480. https://doi.org/10.1080/17408989.2015.1095870

Renshaw, I., Chow, J. Y., Davids, K., & Hammond, J. (2010). A constraints-led perspective to understanding skill acquisition and game play: A basis for integration of motor learning theory and physical education praxis? *Physical Education and Sport Pedagogy*, *15*(2), 117–137. https://doi.org/10.1080/17408980902791586

Renshaw, I., & Chow, J.-Y. (2019). A constraint-led approach to sport and physical education pedagogy. *Physical Education and Sport Pedagogy*, *24*(2), 103–116. https://doi.org/10.1080/17408989.2018.1552676

Renshaw, I., Davids, K., Shuttleworth, R., & Chow, J. (2009). Insights from ecological psychology and dynamical systems theory can underpin a philosophy of coaching. *International Journal of Sport Psychology*, *40*(4), Article 4.

Renshaw, I., & Gorman, A. (2015). Challenges to capturing expertise in field settings. In J. Baker & D. Farrow (Eds.), *Routledge Handbook of Sport Expertise* (pp. 282–294). Routledge. https://www.routledge.com/products/9780415839808

Ribeiro, J., Davids, K., Araújo, D., Guilherme, J., Silva, P., & Garganta, J. (2019). Exploiting Bi-Directional Self-Organizing Tendencies in Team Sports: The Role of the Game Model and Tactical Principles of Play. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02213

Ritchie, D., Hopkins, W. G., Buchheit, M., Cordy, J., & Bartlett, J. D. (2016). Quantification of Training and Competition Load Across a Season in an Elite Australian Football Club. *International Journal of Sports Physiology and Performance*, *11*(4), 474–479. https://doi.org/10.1123/ijspp.2015-0294

Roberts, A. H., Greenwood, D., Humberstone, C., & Raynor, A. J. (2020). Pilot Study on the Reliability of the Coach's Eye: Identifying Talent Throughout a 4-Day Cadet Judo Camp. *Frontiers in Sports and Active Living*, *2*. https://doi.org/10.3389/fspor.2020.596369

Robertson, S. (2020). Man & machine: Adaptive tools for the contemporary performance analyst. *Journal of Sports Sciences*, *38*(18), 2118–2126. https://doi.org/10.1080/02640414.2020.1774143

Robertson, S., Back, N., & Bartlett, J. D. (2016). Explaining match outcome in elite Australian Rules football using team performance indicators. *Journal of Sports Sciences*, *34*(7), 637–644. https://doi.org/10.1080/02640414.2015.1066026

Robertson, S., Bartlett, J. D., & Gastin, P. B. (2017). Red, Amber, or Green? Athlete Monitoring in Team Sport: The Need for Decision-Support Systems. *International Journal of Sports Physiology and Performance*, *12*(s2), S2-79. https://doi.org/10.1123/ijspp.2016-0541

Robertson, S., & Joyce, D. (2019). *Bounded rationality revisited: Making sense of complexity in applied sport science*. SportRxiv. https://doi.org/10.31236/osf.io/yh38j

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019a). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. https://doi.org/10.1080/02640414.2018.1555905

Robertson, S., Spencer, B., Back, N., & Farrow, D. (2019b). A rule induction framework for the determination of representative learning design in skilled performance. *Journal of Sports Sciences*, *37*(11), 1280–1285. https://doi.org/10.1080/02640414.2018.1555905

Roca, A., & Ford, P. R. (2020). Decision-making practice during coaching sessions in elite youth football across European countries. *Science and Medicine in Football*, *4*(4), 263–268. https://doi.org/10.1080/24733938.2020.1755051

Rodacki, A. L., Fowler, N. E., & Bennett, S. J. (2001). Multi-segment coordination: Fatigue effects. *Medicine and Science in Sports and Exercise*, *33*(7), 1157–1167.

Ross, E., Gupta, L., & Sanders, L. (2018). When research leads to learning, but not action in high performance sport. In S. Marcora & M. Sarkar (Eds.), *Progress in Brain Research* (Vol. 240, pp. 201–217). Elsevier. https://doi.org/10.1016/bs.pbr.2018.08.001

Rothwell, M., Davids, K., & Stone, J. (2018). Harnessing socio-cultural constraints on athlete development to create a form of life. *Journal of Expertise*, *1*(1), Article 1. https://www.journalofexpertise.org/articles/volume1_issue1/JoE_2018_1_1_Rothwell_Davids_Stone.html

Rothwell, M., Davids, K., Stone, J., O'Sullivan, M., Vaughan, J., Newcombe, D., & Shuttleworth, R. (2020). A department of methodology can coordinate transdisciplinary sport science support. *Journal of Expertise, 3*(1), Article 1.

Rothwell, M., Stone, J., & Davids, K. (2022). Investigating the athlete-environment relationship in a form of life: An ethnographic study. *Sport, Education and Society*, *27*(1), 113–128. https://doi.org/10.1080/13573322.2020.1815690

Rudd, J. R., Pesce, C., Strafford, B. W., & Davids, K. (2020). Physical Literacy - A Journey of Individual Enrichment: An Ecological Dynamics Rationale for Enhancing Performance and Physical Activity in All. *Frontiers in Psychology, 11*. https://doi.org/10.3389/fpsyg.2020.01904

Rudd, J. R., Woods, C., Correia, V., Seifert, L., & Davids, K. (2021). An ecological dynamics conceptualisation of physical 'education': Where we have been and where we could go next. *Physical Education and Sport Pedagogy*, *26*(3), 293–306. https://doi.org/10.1080/17408989.2021.1886271

Ryoo, M., Kim, N., & Park, K. (2018). Visual analysis of soccer players and a team. *Multimedia Tools and Applications*, *77*(12), 15603–15623. https://doi.org/10.1007/s11042-017-5137-4

Santos, S. D. L., Memmert, D., Sampaio, J., & Leite, N. (2016). The Spawns of Creative Behavior in Team Sports: A Creativity Developmental Framework. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01282

Sarmento, H., Clemente, F. M., Harper, L. D., Costa, I. T. da, Owen, A., & Figueiredo, A. J. (2018). Small sided games in soccer – a systematic review. *International Journal of Performance Analysis in Sport, 18*(5), 693–749. https://doi.org/10.1080/24748668.2018.1517288

Schelling, X., & Robertson, S. (2020). A development framework for decision support systems in high-performance sport. *International Journal of Computer Science in Sport, 19*(1), 1–23.

Schmidt, L., Lebreton, M., Cléry-Melin, M.-L., Daunizeau, J., & Pessiglione, M. (2012). Neural Mechanisms Underlying Motivation of Mental Versus Physical Effort. *PLOS Biology*, *10*(2), e1001266. https://doi.org/10.1371/journal.pbio.1001266

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225–260. https://doi.org/10.1037/h0076770

Schmidt, R. A., Lee, T. D., Winstein, C., Wulf, G., & Zelaznik, H. N. (2018). *Motor Control and Learning: A Behavioral Emphasis*. Human Kinetics.

Seifert, L., Araújo, D., Komar, J., & Davids, K. (2017). Understanding constraints on sport performance from the complexity sciences paradigm: An ecological dynamics framework. *Human Movement Science*, *56*, 178–180. https://doi.org/10.1016/j.humov.2017.05.001

Seifert, L., Button, C., & Davids, K. (2013). Key Properties of Expert Movement Systems in Sport. *Sports Medicine*, *43*(3), 167–178. https://doi.org/10.1007/s40279-012-0011-z

Seifert, L., Komar, J., Barbosa, T., Toussaint, H., Millet, G., & Davids, K. (2014). Coordination Pattern Variability Provides Functional Adaptations to Constraints in Swimming Performance. *Sports Medicine*, *44*(10), 1333–1345. https://doi.org/10.1007/s40279-014-0210-x

Shafizadeh, M., Bonner, S., Fraser, J., & Barnes, A. (2019). Effect of environmental constraints on multi-segment coordination patterns during the tennis service in expert performers. *Journal of Sports Sciences*, *37*(9), 1011–1020. https://doi.org/10.1080/02640414.2018.1538691

Sheehan, W. B., Tribolet, R., Novak, A. R., Fransen, J., & Watsford, M. L. (2021). An assessment of physical and spatiotemporal behaviour during different phases of match play in professional Australian football. *Journal of Sports Sciences*, *39*(19), 2232–2241. https://doi.org/10.1080/02640414.2021.1928408

Sheehan, W. B., Tribolet, R., Spurrs, R., Fransen, J., Novak, A. R., & Watsford, M. L. (2020). Simplifying the complexity of assessing physical performance in professional Australian football.

Science and Medicine in Football, *4*(4), 285–292. https://doi.org/10.1080/24733938.2020.1745264

Sheehan, W. B., Tribolet, R., Watsford, M. L., Novak, A. R., Rennie, M., & Fransen, J. (2020a). Improving the interpretation of skill indicators in professional Australian Football. *Journal of Science and Medicine in Sport*, *23*(9), 872–878. https://doi.org/10.1016/j.jsams.2020.01.016

Sheehan, W. B., Tribolet, R., Watsford, M. L., Novak, A. R., Rennie, M., & Fransen, J. (2022). Tactical analysis of individual and team behaviour in professional Australian Football. *Science and Medicine in Football, 6*(2), 172–180. https://doi.org/10.1080/24733938.2021.1923792

Sheehan, W. B., Tribolet, R., Watsford, M. L., Novak, A. R., Rennie, M. J., & Fransen, J. (2020b). Using cooperative networks to analyse behaviour in professional Australian Football. *Journal of Science and Medicine in Sport*, *23*(3), 291–296. https://doi.org/10.1016/j.jsams.2019.09.012

Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., & Garganta, J. (2016). Practice effects on intra-team synergies in football teams. *Human Movement Science*, *46*, 39–51. https://doi.org/10.1016/j.humov.2015.11.017

Silva, P., Duarte, R., Sampaio, J., Aguiar, P., Davids, K., Araújo, D., & Garganta, J. (2014). Field dimension and skill level constrain team tactical behaviours in small-sided and conditioned games in football. *Journal of Sports Sciences*, *32*(20), 1888–1896. https://doi.org/10.1080/02640414.2014.961950

Silva, P., Esteves, P., Correia, V., Davids, K., Araújo, D., & Garganta, J. (2015). Effects of manipulations of player numbers vs. Field dimensions on inter-individual coordination during small-sided games in youth football. *International Journal of Performance Analysis in Sport*, *15*(2), 641–659. https://doi.org/10.1080/24748668.2015.11868821

Silva, P., Travassos, B., Vilar, L., Aguiar, P., Davids, K., Araújo, D., & Garganta, J. (2014). Numerical Relations and Skill Level Constrain Co-Adaptive Behaviors of Agents in Sports Teams. *PLoS ONE*, *9*(9). https://doi.org/10.1371/journal.pone.0107112

Silva, P., Vilar, L., Davids, K., Araújo, D., & Garganta, J. (2016). Sports teams as complex adaptive systems: Manipulating player numbers shapes behaviours during football small-sided games. *SpringerPlus*, *5*(1), 191. https://doi.org/10.1186/s40064-016-1813-5

Simon, H., & Chase, W. (1988). Skill in Chess. In D. Levy (Ed.), *Computer Chess Compendium* (pp. 175–188). Springer. https://doi.org/10.1007/978-1-4757-1968-0_18

Simonoff, J. S. (1996). *Smoothing Methods in Statistics*. Springer-Verlag. https://doi.org/10.1007/978-1-4612-4026-6

Soderstrom, N. C., & Bjork, R. A. (2015). Learning Versus Performance: An Integrative Review. *Perspectives on Psychological Science*, *10*(2), 176–199. https://doi.org/10.1177/1745691615569000

Solanki, S. K., & Patel, J. T. (2015). A Survey on Association Rule Mining. *2015 Fifth International Conference on Advanced Computing Communication Technologies*, 212–216. https://doi.org/10.1109/ACCT.2015.69

Sparks, M., Coetzee, B., & Gabbett, J. T. (2016). Variations in high-intensity running and fatigue during semi-professional soccer matches. *International Journal of Performance Analysis in Sport*, *16*(1), 122–132. https://doi.org/10.1080/24748668.2016.11868875

Spencer, B., Bedin, T., Farrow, D., & Jackson, K. (2018). A method for evaluating player decision-making in the Australian football league. *Proceedings of 14th Australasian Conference on Mathematics and Computers in Sport*, 7–12.

Spencer, B., Hawkey, M., & Robertson, S. (2019). Using contextual player movement and spatial control to analyse player passing trends in football. *Barça Sport. Analytics Summit*, 1–12.

Spencer, B., Jackson, K., Bedin, T., & Robertson, S. (2019). Modeling the Quality of Player Passing Decisions in Australian Rules Football Relative to Risk, Reward, and Commitment. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.01777

Spencer, B., Morgan, S., Zeleznikow, J., & Robertson, S. (2017). Measuring Player Density in Australian Rules Football Using Gaussian Mixture Models. *Complex Systems in Sport, International Congress Linking Theory and Practice*, *5*, 172–174. https://doi.org/10.3389/978-2-88945-310-8

Starkes, J. L., Deakin, J. M., Allard, F., Hodges, N. J., & Hayes, A. (1996). Deliberate practice in sports: What is it anyway. *The Road to Excellence: The Acquisition of Expert Performance in the Arts and Sciences, Sports, and Games*, 81–106.

Stein, M., Janetzko, H., Seebacher, D., Jäger, A., Nagel, M., Hölsch, J., Kosub, S., Schreck, T., Keim, D. A., & Grossniklaus, M. (2017). How to Make Sense of Team Sport Data: From Acquisition to Data Modeling and Research Aspects. *Data*, *2*(1), Article 1. https://doi.org/10.3390/data2010002

Stone, J. A., Rothwell, M., Shuttleworth, R., & Davids, K. (2021). Exploring sports coaches' experiences of using a contemporary pedagogical approach to coaching: An international perspective. *Qualitative Research in Sport, Exercise and Health*, *13*(4), 639–657. https://doi.org/10.1080/2159676X.2020.1765194

Strafford, B. W., van der Steen, P., Davids, K., & Stone, J. A. (2018). Parkour as a Donor Sport for Athletic Development in Youth Team Sports: Insights Through an Ecological Dynamics Lens. *Sports Medicine - Open*, *4*(1), 21. https://doi.org/10.1186/s40798-018-0132-5

Suárez, E., Pérez, C. M., Rivera, R., & Martínez, M. N. (2017). *Applications of Regression Models in Epidemiology*. John Wiley & Sons.

Sullivan, C., Bilsborough, J. C., Cianciosi, M., Hocking, J., Cordy, J. T., & Coutts, A. J. (2014). Factors Affecting Match Performance in Professional Australian Football. *International Journal of Sports Physiology and Performance*, *9*(3), 561–566. https://doi.org/10.1123/ijspp.2013-0183

Sullivan, M. O., Woods, C. T., Vaughan, J., & Davids, K. (2021). Towards a contemporary player learning in development framework for sports practitioners. *International Journal of Sports Science & Coaching*, *16*(5), 1214–1222. https://doi.org/10.1177/17479541211002335

Sweeting, A. J., Aughey, R. J., Cormack, S. J., & Morgan, S. (2017). Discovering frequently recurring movement sequences in team-sport athlete spatiotemporal data. *Journal of Sports Sciences*, *35*(24), 2439–2445. https://doi.org/10.1080/02640414.2016.1273536

Taki, T., Hasegawa, J., & Fukumura, T. (1996). Development of motion analysis system for quantitative evaluation of teamwork in soccer games. *Proceedings of 3rd IEEE International Conference on Image Processing*, *3*, 815–818 vol.3. https://doi.org/10.1109/ICIP.1996.560865

Teune, B., Spencer, B., Sweeting, A. J., Woods, C., Inness, M., & Robertson, S. (2021). Application of a continuous pressure metric for Australian football. *Journal of Sports Sciences*, *39*(13), 1548–1554. https://doi.org/10.1080/02640414.2021.1886416

Teune, B., Woods, C., Sweeting, A., Inness, M., & Robertson, S. (2021a). The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. *European Journal of Sport Science*, *22*(8). https://doi.org/10.1080/17461391.2021.1958011

Teune, B., Woods, C., Sweeting, A., Inness, M., & Robertson, S. (2021). The influence of environmental and task constraint interaction on skilled behaviour in Australian Football. *European Journal of Sport Science.* https://doi.org/10.1080/17461391.2021.1958011

Teune, B., Woods, C., Sweeting, A., Inness, M., & Robertson, S. (2022). A method to inform team sport training activity duration with change point analysis. *PLOS ONE*, *17*(3), e0265848. https://doi.org/10.1371/journal.pone.0265848

Therneau, T., & Atkinson, B. (2022). *rpart: Recursive Partitioning and Regression Trees.* (R package version 4.1.16). https://CRAN.R-project.org/package=rpart

Timmerman, E. A., Farrow, D., & Savelsbergh, G. J. (2017). The effect of manipulating task constraints on game performance in youth field hockey. *International Journal of Sports Science & Coaching*, *12*(5), 588–594. https://doi.org/10.1177/1747954117727659

Timmerman, E. A., Savelsbergh, G. J. P., & Farrow, D. (2019). Creating Appropriate Training Environments to Improve Technical, Decision-Making, and Physical Skills in Field Hockey. *Research Quarterly for Exercise and Sport*, *90*(2), 180–189. https://doi.org/10.1080/02701367.2019.1571678

Torrents, C., Balagué, N., Ric, Á., & Hristovski, R. (2021). The motor creativity paradox: Constraining to release degrees of freedom. *Psychology of Aesthetics, Creativity, and the Arts*, *15*(2), 340–351. https://doi.org/10.1037/aca0000291

Torrents, C., Ric, A., Hristovski, R., Torres-Ronda, L., Vicente, E., & Sampaio, J. (2016). Emergence of Exploratory, Technical and Tactical Behavior in Small-Sided Soccer Games when Manipulating the Number of Teammates and Opponents. *PLOS ONE*, *11*(12), e0168866. https://doi.org/10.1371/journal.pone.0168866

Torres-Ronda, L., Beanland, E., Whitehead, S., Sweeting, A., & Clubb, J. (2022). Tracking Systems in Team Sports: A Narrative Review of Applications of the Data and Sport Specific Analysis. *Sports Medicine - Open*, *8*(1), 15. https://doi.org/10.1186/s40798-022-00408-z

Travassos, B., Gonçalves, B., Marcelino, R., Monteiro, R., & Sampaio, J. (2014). How perceiving additional targets modifies teams' tactical behavior during football small-sided games. *Human Movement Science*, *38*, 241–250. https://doi.org/10.1016/j.humov.2014.10.005

Tribolet, R., Sheehan, W. B., Novak, A. R., Rennie, M. J., Watsford, M. L., & Fransen, J. (2022). Match simulation practice may not represent competitive match play in professional Australian football. *Journal of Sports Sciences*, *40*(4), 413–421. https://doi.org/10.1080/02640414.2021.1995245

Tribolet, R., Sheehan, W. B., Novak, A. R., Watsford, M. L., & Fransen, J. (2021). Factors associated with cooperative network connectedness in a professional Australian football small-sided game. *Science and Medicine in Football*. https://doi.org/10.1080/24733938.2021.1991584

Trounson, K. M., Busch, A., Collier, N. F., & Robertson, S. (2020). Effects of acute wearable resistance loading on overground running lower body kinematics. *PLOS ONE*, *15*(12), e0244361. https://doi.org/10.1371/journal.pone.0244361

Tsutsui, S., Satoh, M., & Yamamoto, K. (2013). Contextual Interference Modulated by Pitcher Skill Level. *International Journal of Sport and Health Science*, *11*, 68–75. https://doi.org/10.5432/ijshs.201211

Turvey, M. T. (1990). Coordination. *American Psychologist*, *45*(8), 938–953. https://doi.org/10.1037/0003-066X.45.8.938

Uehara, L., Button, C., Araujo, D., Renshaw, I., & Davids, K. (2018). The role of informal, unstructured practice in developing football expertise: The case of Brazilian Pelada. *Journal of Expertise*, *1*(3), Article 3.

Vaeyens, R., Lenoir, M., Williams, A. M., Mazyn, L., & Philippaerts, R. M. (2007). The Effects of Task Constraints on Visual Search Behavior and Decision-Making Skill in Youth Soccer Players. *Journal of Sport and Exercise Psychology*, *29*(2), 147–169. https://doi.org/10.1123/jsep.29.2.147

Vaeyens, R., Lenoir, M., Williams, A. M., & Philippaerts, R. M. (2008). Talent Identification and Development Programmes in Sport. *Sports Medicine*, *38*(9), 703–714. https://doi.org/10.2165/00007256-200838090-00001

Varley, M. C., Elias, G. P., & Aughey, R. J. (2012). Current Match-Analysis Techniques' Underestimation of Intense Periods of High-Velocity Running. *International Journal of Sports Physiology and Performance*, *7*(2), 183–185. https://doi.org/10.1123/ijspp.7.2.183

Varley, M. C., Gabbett, T., & Aughey, R. J. (2014). Activity profiles of professional soccer, rugby league and Australian football match play. *Journal of Sports Sciences*, *32*(20), 1858–1866. https://doi.org/10.1080/02640414.2013.823227

Vaughan, J., Mallett, C. J., Davids, K., Potrac, P., & López-Felip, M. A. (2019). Developing Creativity to Enhance Human Potential in Sport: A Wicked Transdisciplinary Challenge. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02090

Vaughan, J., Mallett, C. J., Potrac, P., López-Felip, M. A., & Davids, K. (2021). Football, Culture, Skill Development and Sport Coaching: Extending Ecological Approaches in Athlete Development Using the Skilled Intentionality Framework. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.635420

Verhoeff, W., Millar, S. K., & Oldham, T. (2018). Constraints-Led Approach to Coaching the Power Clean. *ISBS Proceedings Archive*, *36*(1), 1036.

Vickery, W., & Nichol, A. (2020). What actually happens during a practice session? A coach's perspective on developing and delivering practice. *Journal of Sports Sciences*, *38*(24), 2765–2773. https://doi.org/10.1080/02640414.2020.1799735

Vilar, L., Araújo, D., Davids, K., & Button, C. (2012). The Role of Ecological Dynamics in Analysing Performance in Team Sports: *Sports Medicine*, *42*(1), 1–10. https://doi.org/10.2165/11596520-000000000-00000

Vilar, L., Araújo, D., Davids, K., Correia, V., & Esteves, P. T. (2013). Spatial-temporal constraints on decision-making during shooting performance in the team sport of futsal. *Journal of Sports Sciences*, *31*(8), 840–846. https://doi.org/10.1080/02640414.2012.753155

Vilar, L., Esteves, P. T., Travassos, B., Passos, P., Lago-Peñas, C., & Davids, K. (2014). Varying Numbers of Players in Small-Sided Soccer Games Modifies Action Opportunities during Training. *International Journal of Sports Science & Coaching*, *9*(5), 1007–1018. https://doi.org/10.1260/1747-9541.9.5.1007

Ward, P., Hodges, N. J., Starkes, J. L., & Williams, M. A. (2007). The road to excellence: Deliberate practice and the development of expertise. *High Ability Studies*, *18*(2), 119–153. https://doi.org/10.1080/13598130701709715

Warren, W. H. (2006). The dynamics of perception and action. *Psychological Review*, *113*(2), 358–389. https://doi.org/10.1037/0033-295X.113.2.358

Wedding, C., Woods, C. T., Sinclair, W. H., Gomez, M. A., & Leicht, A. S. (2021). Analysis of styles of play according to season and end of season rank in the National Rugby League. *Journal of Science and Medicine in Sport*, *24*(2), 206–210. https://doi.org/10.1016/j.jsams.2020.09.006

Welc, J., & Esquerdo, P. J. R. (2018). Basics of Regression Models. In J. Welc & P. J. R. Esquerdo (Eds.), *Applied Regression Analysis for Business: Tools, Traps and Applications* (pp. 1–6). Springer International Publishing. https://doi.org/10.1007/978-3-319-71156-0_1

Wijnants, M., Cox, R., Hasselman, F., Bosman, A., & Van Orden, G. (2012). A Trade-Off Study Revealing Nested Timescales of Constraint. *Frontiers in Physiology*, *3*, 116. https://doi.org/10.3389/fphys.2012.00116

Williams, A. M., & Ford, P. R. (2009). Promoting a skills-based agenda in Olympic sports: The role of skill-acquisition specialists. *Journal of Sports Sciences*, *27*(13), 1381–1392. https://doi.org/10.1080/02640410902874737

Williams, A. M., & Hodges, N. J. (2005). Practice, instruction and skill acquisition in soccer: Challenging tradition. *Journal of Sports Sciences*, *23*(6), 637–650. https://doi.org/10.1080/02640410400021328

Woods, C. T., Araújo, D., Davids, K., & Rudd, J. (2021). From a Technology That Replaces Human Perception–Action to One That Expands It: Some Critiques of Current Technology Use in Sport. *Sports Medicine - Open*, *7*(1), 76. https://doi.org/10.1186/s40798-021-00366-y

Woods, C. T., & Davids, K. (2021). “You Look at an Ocean; I See the Rips, Hear the Waves, and Feel the Currents”: Dwelling and the Growth of Enskiled Inhabitant Knowledge. *Ecological Psychology*, *33*(3–4), 279–296. https://doi.org/10.1080/10407413.2021.1965481

Woods, C. T., Jarvis, J., & McKeown, I. (2019). Differences between Elite and Semi-Elite Australian Football Conceptualised through the Lens of Ecological Dynamics. *Sports*, *7*(7), 159. https://doi.org/10.3390/sports7070159

Woods, C. T., McKeown, I., O’Sullivan, M., Robertson, S., & Davids, K. (2020). Theory to Practice: Performance Preparation Models in Contemporary High-Level Sport Guided by an Ecological Dynamics Framework. *Sports Medicine - Open*, *6*(1), 36. https://doi.org/10.1186/s40798-020-00268-5

Woods, C. T., McKeown, I., Rothwell, M., Araújo, D., Robertson, S., & Davids, K. (2020). Sport Practitioners as Sport Ecology Designers: How Ecological Dynamics Has Progressively Changed Perceptions of Skill “Acquisition” in the Sporting Habitat. *Frontiers in Psychology*, *11*, 654. https://doi.org/10.3389/fpsyg.2020.00654

Woods, C. T., McKeown, I., Shuttleworth, R. J., Davids, K., & Robertson, S. (2019). Training programme designs in professional team sport: An ecological dynamics exemplar. *Human Movement Science*, *66*, 318–326. https://doi.org/10.1016/j.humov.2019.05.015

Woods, C. T., Robertson, S., & Collier, N. F. (2017). Evolution of game-play in the Australian Football League from 2001 to 2015. *Journal of Sports Sciences*, *35*(19), 1879–1887. https://doi.org/10.1080/02640414.2016.1240879

Woods, C. T., Robertson, S., Collier, N. F., Swinbourne, A. L., & Leicht, A. S. (2018). Transferring an Analytical Technique from Ecology to the Sport Sciences. *Sports Medicine*, *48*(3), 725–732. https://doi.org/10.1007/s40279-017-0775-2

Woods, C. T., Rothwell, M., Rudd, J., Robertson, S., & Davids, K. (2021). Representative co-design: Utilising a source of experiential knowledge for athlete development and performance preparation. *Psychology of Sport and Exercise*, *52*, 101804. https://doi.org/10.1016/j.psychsport.2020.101804

Woods, C. T., Rudd, J., Araújo, D., Vaughan, J., & Davids, K. (2021). Weaving Lines of Inquiry: Promoting Transdisciplinarity as a Distinctive Way of Undertaking Sport Science Research. *Sports Medicine - Open*, *7*(1), 55. https://doi.org/10.1186/s40798-021-00347-1

Woods, C. T., Rudd, J., Gray, R., & Davids, K. (2021). Enskilment: An Ecological-Anthropological Worldview of Skill, Learning and Education in Sport. *Sports Medicine - Open*, *7*(1), 33. https://doi.org/10.1186/s40798-021-00326-6

Woods, C. T., Rudd, J., Robertson, S., & Davids, K. (2020). Wayfinding: How Ecological Perspectives of Navigating Dynamic Environments Can Enrich Our Understanding of the Learner and the Learning Process in Sport. *Sports Medicine - Open*, *6*(1), 51. https://doi.org/10.1186/s40798-020-00280-9

Woods, C. T., Sinclair, W., & Robertson, S. (2017). Explaining match outcome and ladder position in the National Rugby League using team performance indicators. *Journal of Science and Medicine in Sport*, *20*(12), 1107–1111. https://doi.org/10.1016/j.jsams.2017.04.005

Wulf, G., & Lewthwaite, R. (2016). Optimizing performance through intrinsic motivation and attention for learning: The OPTIMAL theory of motor learning. *Psychonomic Bulletin & Review*, *23*(5), 1382–1414. https://doi.org/10.3758/s13423-015-0999-9

Wulf, G., & Shea, C. H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin & Review*, *9*(2), 185–211. https://doi.org/10.3758/BF03196276

Yearby, T., Myszka, S., Roberts, W. M., Woods, C. T., & Davids, K. (2022). Applying an ecological approach to practice design in American football: Some case examples on best practice. *Sports Coaching Review*. https://doi.org/10.1080/21640629.2022.2057698

Zeileis, A., & Grothendieck, G. (2005). zoo: S3 Infrastructure for Regular and Irregular Time Series. *Journal of Statistical Software*, *14*(1), Article 1. https://doi.org/10.18637/jss.v014.i06

Zelič, I., Kononenko, I., Lavrač, N., & Vuga, V. (1997). Induction of Decision Trees and Bayesian Classification Applied to Diagnosis of Sport Injuries. *Journal of Medical Systems*, *21*(6), 429–444. https://doi.org/10.1023/A:1022880431298

Zhang, X.-D. (2020). Machine Learning. In X.-D. Zhang (Ed.), *A Matrix Algebra Approach to Artificial Intelligence* (pp. 223–440). Springer. https://doi.org/10.1007/978-981-15-2770-8_6

APPENDICES

APPENDIX A – APPROVAL TO CONDUCT RESEARCH

APPENDIX A.1 Victoria University Human Research Ethics Application Approval

From: "quest.noreply@vu.edu.au" <quest.noreply@vu.edu.au>
Date: Tuesday, 23 February 2021 at 11:46 am
To: Sam Robertson <Sam.Robertson@vu.edu.au>
Cc: Alice Sweeting <Alice.Sweeting@vu.edu.au>, Carl Woods <Carl.Woods@vu.edu.au>, Mathew Inness <Mathew.Inness@vu.edu.au>
Subject: Quest Ethics Notification - Application Process Finalised - Application Approved

Dear PROF SAMUEL ROBERTSON,

Your ethics application has been formally reviewed and finalised.

» Application ID: HRE20-138
» Chief Investigator: PROF SAMUEL ROBERTSON
» Other Investigators:
» Application Title: A constraints-led approach to informing Australian Football training design and its relationship with skilled behaviour
» 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; 23/02/2021.

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

-
This is an automated email from an unattended email address. Do not reply to this address.