A method to quantify external training and match load in elite Australian Football players

By

JACKIE E. DOWELL

Bachelor of Sport Science – Exercise Science (Honours)

This thesis is submitted in partial fulfillment of the requirements for the award of

Doctor of Philosophy

Victoria University, Melbourne, Australia

OCTOBER 2023

ABSTRACT

Individual performance can be defined as a players ability to complete the desired task at a substantial quality whereby winning is the ultimate goal. It is very hard to predict performance through training in sports such as Australian Football (AF) given their dynamic and complex nature. Any training monitoring tool or data analysis technique that can provide any insight into match performance or correlation can substantially assist practitioners to get a competitive advantage over their opponents, ultimately leading to short term and long-term success.

The primary aims of this thesis were to investigate the extent to which commonly used training monitoring tools demonstrate a relationship with performance when measured from both a subjective and objective perspective. Additionally, it aims to develop a novel approach to visually representing the accumulation of volume across the intensity spectrum for various comparisons throughout the pre-season and in-season phases of the highest level of AF being the Australian Football League (AFL). This new data analysis technique was implemented as it allows for quantification of the distribution of volume accumulated providing more practical insights for practitioners, compared to previous studies whereby the distribution has simply been modelled visually. The specific aims of each study are as follows.

Study 1: to determine which characteristic/s if any, have a relationship with match performance identified through Champion Data© rating points and coaches subjective player ratings. Forty AF players from the same club (25 ± 4 yr) were monitored across the 2019 AFL season. Mixed models were used to compare each of these performance ratings with wellness scores and Global Navigation Satellite System (GNSS) metrics such as total distance, surge distance, sprint distance, total high-speed running distance, work rate and maximum velocity. There were two statistically significant relationships identified, wellness energy scores and coaches subjective ratings and wellness soreness scores and Champion Data© rating points. Neither relationship provided meaningful results given both relationships were in a negative direction whereby the findings are not something to be promoted with players. The lack of findings suggest more sophisticated analysis techniques are required investigating suitable metrics that assess performance.

Study 2: to implement the new analytical approach and determine the cumulative distribution of volume across the intensity spectrum for an entire home and away season of AF, specifically investigating the accumulation differences between competition levels (AFL vs Victorian Football League (VFL)) and the duration of the match. Thirty-three AF players from the same club (24.4 ± 4.3 yr) were monitored across the 2021 season. The data collected was processed into absolute values with a one minute moving average applied whereby the observations were categorised into 10 $m.min^{-1}$ and 5 $m \cdot min^{-1} \cdot s^{-1}$ zones for speed and acceleration respectively and the total distance in each zone was calculated. Quadratic models were then created for each player for each quarter which was then summarised by competition level and quarter of the game for analysis. A clear difference in speed and acceleration between the duration of the match and competition levels were identified. This study identified AFL is played at a higher intensity than VFL and within AF matches, quarter one is the most intense with a decline across the duration of the game in both speed and acceleration.

Study 3: to expand on the analysis used in the previous study and apply this technique to examine the distribution of volume across an AF pre-season and investigate the volume during different pre-season phases and training drill modalities. Forty-three AF players from the same club (24.4 ± 4.3 yr) were monitored across the 2022 AFL pre-season period, spanning November 2021 to March 2022. The same data analysis technique was used as in study 2, with the only variation being the data analysed. The data was categorised in three pre-season phases, pre-Christmas, post-Christmas and pre-competition and four training drill modalities, fundamentals, structure, game plan and conditioning. Training drill modalities were categorised based on predicted work rates identified by the clubs high performance manager. This study identified that the post-Christmas phase exposes players to the greatest volume of pre-season at a high intensity. Within training drills, conditioning drills accumulate the greatest acceleration while game plan drills expose players to the highest intensity.

Study 4: to continue expanding on the previously used analysis technique and apply it to in-season, specifically examining the distribution of volume between different match turnaround lengths and whether matches or training accumulate the greatest volume. Forty-three AF players from the same club (24.4 ± 4.3 yr) were monitored across the 2022 AFL home and away season. The same data analysis technique was used as per study 2 and 3, where the comparison was changed to three between match turnaround lengths (<7-day, 7-8-day and >8-day) and matches versus training. Within the week, matches regardless of the between match turnaround length accumulate the greatest volume. When examining match volume specifically across the different turnaround lengths, greater impulse is achieved in matches where the between match turnaround length is >8 days.

General conclusions: Overall the data from this thesis builds upon the known importance of acceleration in AF and provides quantifiable results that can be utilised in training design, in designing drills based off of these findings. Through understanding the differences between match quarters this may drive a conversation around how training can improve to limit the decline observed between quarter one through four. It can also assist at the sub-elite levels by providing benchmarks for the top speeds and impulse achieved at the elite level, to allow players to train towards. These findings can also confirm training periodisation plans for practitioners whereby, intentions are proven or disproven to be true based on the cumulation observed as the analysis techniques used in these studies can be adapted and applied in many sports.

STATEMENT OF AUTHORSHIP

I, Jackie Dowell, declare that the PhD thesis entitled 'Quantifying running volume and understanding individual responses in elite Australian Football players' is no more than 80,000 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.

Signature: [redacted] **Date:** 13/10/23

Ethics Declaration

All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee (VUHREC) - HRE20-203.

Signature [redacted] **Date:** 13/10/23

ACKNOWLEDGMENTS

Through the rollercoaster that this PhD has been, there have been a large amount of people that have help made this submission possible and made a substantial contribution in my learning and development.

Firstly, to my supervisors, Dr. Grant Duthie, Professor Sam Robertson and Professor Robert Aughey. Without the assistance of you all this submission wouldn’t have been possible. There have been more challenges and setbacks then I could have imagined throughout the duration of my PhD but you all played a crucial part at different stages to help get this across the line.

Grant, despite being in different states you have been there and available at any turn I have needed help whether it be for this work or professional advice, you have provided so much guidance and taught me so much. From starting out looking at your spreadsheets and having no clue to finally understanding them and bothering you with the countless questions along the way, it took a while, but we got there and I have improved my data analytics skills because of this. Rob, for sticking with me for six years now, I have learnt so much. You have helped me constantly improve my writing and professionalism from where it first began. You have always challenged me and made me critically analyse my work and answer the tough questions which has helped me both professionally and academically. Sam, for stepping in at the eleventh hour and helping reassure me when I thought it was all over and it wasn’t possible to finish this, I am so thankful and no words will do it justice as the final stages of this submission would not be possible without you.

A special mention goes out to Heidi Compton, you played such a crucial role in this thesis and also helped me navigate first steps outside of the thesis and gaining employment. You provided so much help at a time when I felt the most lost throughout this process and without formally being a supervisor, you did this all from the kindness of your heart and I will always be thankful for that. As well as this you also helped me develop my coding skills which is a great asset to continue on with my work.

To Neil Collier, thank you for your patience and guidance in teaching me the world of coding and stepping me through all of the analysis for my first study. I learnt so much from you from our weekly meetings that I will always value.

To the Collingwood Football Club, thank you for bringing me into the club and allowing me to complete this project and eventually provide me with employment. There are so many people that have contributed to my development over the time I have been at the club. I'd like to specially thank Victor Nguyen for showing me the ropes when I first started and being a constant support through my time at the club. To Jarrod Wade for bringing me back into the club and providing me with the opportunity to work AFL game days which was always a dream and offering me the position within the AFLW program. To, Paul Turk for teaching me so much and having so much trust in me and allowing a young sports scientist to run high-performance for an AFLW game day in my first season was an opportunity I will always be grateful for. You are a great mentor to learn from and I am so thankful to be staying on with the club and working alongside you for another season.

Finally, to my family for the encouragement, reassurance and support throughout the entire duration of this PhD, for the countless times I felt like I couldn't do it and wanted to give up, you provided the support to keep me going.

This research was supported by a VU Research Training Program (RTP) Scholarship.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

±	Plus/minus
a	Position of the curve
AF	Australian football
AFL	Australian Football League
b	Linear coefficient
c	Intercept
CI	Confidence interval
CL	Confidence limit
cm	Centimetre
CR	Category ratio
csv	Comma separated values file
DBSCAN	Density-based spatial clustering of applications with noise
ES	Effect size
GNSS	Global navigation satellite system
GPS	Global positioning system
Hz	Hertz
kg	Kilogram
km	Kilometre
$km{\cdot}hr^{-1}$	Kilometre per hour
$kN{\cdot}s^{-1}$	Kilonewton per second
LPS	Local position system
m	Meter
$m{\cdot}min^{-1}{\cdot}s^{-1}$	Meter per minute per second
$m{\cdot}s^{-2}$	Meter per second per second
$m{\cdot}min\text{-}^{1}$	Meter per minute
$N{\cdot}s^{-1}$	Newton per second
POMS	Profile of mood state
RESTQ-Sport	Recovery stress questionnaire sport
RPE	Rating of perceived exertion
s	Second
s-RPE	Session-rating of perceived exertion

SD	Standard deviation
SE	Standard estimate error
SSG	Small sided games
STS	Soft tissue soreness
VFL	Victorian Football League
yr	Year

CHAPTER 1. GENERAL INTRODUCTION

1.1 Background

Team sport players, specifically those in AF are exposed to very high training loads accumulated across the week and consequentially season compared to other football codes (Johnston et al., 2018). This high training load is mainly expressed through a greater total volume 12,620 ± 1872 m in AF compared to, rugby league (6276 ± 1950 m) and soccer (10,274 ± 946 m) and more high velocity running (AF; 1322 ± 374 m, rugby league; 327 ± 168 m and soccer; 517 ± 239 m) (Varley et al., 2014). Given the volume of running accumulated both in training and competition, sufficient recovery is an important component of the training program that is factored into training prescription based on the periodised model (Bompa & Haff, 2009; deCunanan et al., 2018; Mujika et al., 2018). Within a sport such as AF, periodisation is a common tool used by practitioners to expose players to appropriate training stimulus to prepare them for competition, but also not increase the risk of injury given the short timeline between matches. This relationship has been described as the "training-injury paradox" (Gabbett, 2016) and reflects the importance of ensuring players are adequately prepared for the demands of training and competition.

In AF, the highest competitive level is called the AFL, which is a competitive season that can be split into two fundamental phases, being pre-season and in-season (Moreira et al., 2015). Within these phases, dependent on the specific periodisation of the club, there can be multiple mesocycles that consist of shorter duration phases with individualised focuses tailored to the stage of the competitive season (Bompa & Haff, 2009; Moreira et al., 2015; Ritchie et al., 2016). For example, the pre-season phase in AF can be categorised by three different mesocycles, general preparation (pre-Christmas), specific preparation (post-Christmas) and pre-competition phase (Bompa & Haff, 2009; Moreira et al., 2015; Ritchie et al., 2016). During each of these mesocycles there is a clear shift between training prescription of these phases as the overarching goal is to prepare for competition (Buchheit et al., 2015).

As different periodisation phases are targeted at eliciting different responses, it is expected that training needs to be monitored in some capacity to account for these responses (Halson, 2014; Moreira et al., 2015). There are multiple monitoring tools available so the issue becomes, determining what monitoring tools are actually necessary and meaningful for practitioners to collect (Australian Academy of Science, 2022). It is essential that data is interpreted or analysed in a meaningful way that can infer descriptive reporting that can be utilised for other practitioners or coaches (Torres-Ronda et al., 2022). There are monitoring tools readily available for interpretation to generate reports, however, there is also an increasing prevalence of analysis techniques being investigated and expanded on through sports scientists embedded throughout elite sport (Torres-Ronda et al., 2022). Subsequently, during the different periodisation phases training needs to be monitored for different responses such as, load tolerance, overtraining and fatigue (Bompa & Haff, 2009). This requires meaningful tools, data interpretation and analysis, with a focus on practical application by practitioners and coaches.

The most common monitoring tool utilised in AF at the elite level is the Global Navigation Satellite Systems (GNSS). As part of the withstanding contract between the AFL and Catapult Sports (Melbourne, Victoria) Catapult Vector S7 units are worn by all players within all teams within the AFL. As part of this agreement Catapult provides a console and cloud based platform that delivers summative data including metrics such as; distance (m), high speed running (m), velocity ($km.hr^{-1}$ or $m.s^{-1}$), accelerations, decelerations and sprint efforts. Using summative reports to generate inferences about the training load that players are exposed to, comes with limitations, given summative data can reduce data integrity by eliminating data points (Wilke, 2019). Within the Catapult console there is also the ability to export raw data files from the console to be used for practitioners own analysis. This allows calculations of maximal mean running speed and acceleration, while also allows the distribution of running to be examined. To overcome limitations such as lost data points, there are analysis techniques that can be employed which keep the integrity of the data by utilising all data points eliminating the need for summating data which are applied in the studies throughout this thesis (Wilke, 2019).

This thesis aimed to investigate the relationship between variables provided from current training monitoring tools used within a professional AFL club. Subsequently, this investigation sought to provide insights into determining which monitoring tools should be consistently employed for the entire squad. Further, the research implemented new data analysis techniques that utilised the cumulative distribution across the intensity spectrum. This analysis was conducted on both match conditions and training conditions. The match analysis included quantification of the effects of competition level, match quarters, and match turnaround duration. Training analysis encompassed the different phases of the season and the different training drill modalities. Understanding the distribution of training volume relative to intensity is valuable for practitioners as it not only impacts the training load prescribed during the training week, aligning with the periodisation model, but also indicates whether certain players might require more focused recovery attention. By investigating these aspects, the research aims to contribute to better decision-making regarding training monitoring tools, training load management, and athlete-specific recovery strategies.

The transformations in training volume and intensity within the pre-season phases of AFL have been documented (Moreira et al., 2015; Ritchie et al., 2016). However, there is a lack of comprehensive documentation of how volume and intensity vary within the different training modalities within the pre-season period. This gap in knowledge can likely be attributed to the distinctive approaches each club employs in training prescription, coupled with the reluctance of clubs to divulge proprietary drill designs and confidential training volume information. While previous research does acknowledge disparities between skills-based training, conditioning, and resistance training (Ritchie et al., 2016), no study to date has delved into the intricate array of training drills constituting skills training. Previous research in AF has pinpointed numerous skill-based drills geared towards distinct goals, be they are technical, tactical, or a combination of both (Corbett et al., 2017). However, a crucial void remains in the investigation of volume accumulation concerning speed and acceleration across these diverse training drill modalities. This discrepancy is noteworthy given the acknowledged significance of acceleration, especially in the realm of AF (Aughey, 2010; Johnston et al., 2015d). Gaining a comprehensive understanding of the cumulative speed and acceleration volumes attributed to individual training drills holds tangible practical value in training prescription. Recognising the imperative nature of replicating match demands during training (Barris et al., 2013; Pinder et al., 2011), insights into the speed and acceleration volumes amassed by specific training drills can substantially aid practitioners in aligning training objectives with targeted match demands. This knowledge empowers those responsible for designing training regimens or overseeing athlete load to select and tailor training drills more effectively.

Overall, understanding the distribution of training volume has the potential in assisting and providing context around how speed and acceleration are accumulated throughout these different comparisons instead of simply providing a summary statistic. Therefore, the overall purpose of this thesis is to firstly, determine any valid monitoring tools already being used to predict match performance secondly, use a novel approach to determine the cumulative distribution of speed and acceleration across the intensity spectrum for multiple variables to provide further context which can assist with training prescription in AF. By establishing the distribution of volume, this can assist practitioners in making informed decisions in training and matches.

1.2 Objectives

Training monitoring is a common process in elite sport, whereby data is collected to quantify training in team sports, to provide information to assist practitioners with understanding athletes responses to training prescription, recovery and performance. The overall aim of this thesis is to quantify running volume in AF and implement a new analysis technique to provide a visual distribution of volume for both speed and acceleration across the intensity spectrum. This analysis can then be used to provide context to overall assist with training prescription and design employed at the AF club. The relationship (or lack of relationship) between the training week and match performance can further support the implementation of monitoring tools within the AF club or their removal.

The findings from these collective studies can provide practitioners with a greater understanding firstly, whether any of the existing training monitoring tools have a direct correlation with performance. Secondly, it will provide information around the distribution of volume across varied conditions in AF, such as the effects of different competition levels (AFL vs VFL), match quarters (one through four), pre-season phases (the three different mesocycles), training drill modalities (four different training drill classification types used by the AF club investigated) and lastly, between match turnaround length (short, medium and long turnaround lengths experience during the 2022 AFL home and away season).

The use of cumulative distribution across the studies will provide a greater scope of understanding compared to previous research that has investigated the same or similar comparisons. This understanding will assist practitioners and/or coaches in regard to training prescription and the effect of various conditions i.e., turnaround length and competition level, on performance identified through the one minute maximal mean speed and accelerations achieved and whether these maximal means are maintained across the various comparisons. This knowledge can practically assist with training design in regard to specific drill selection based on what said drills accumulate, or providing further context to how volume is accumulated throughout a match. Understanding the accumulation of speed and acceleration during a match can quantify the total volume players accumulate and the interpersonal variation that exists. The quantification of volume and the comparison of this amongst players, through this novel analysis technique can provide specific information as to which speed or acceleration intensity volume is lacking. Therefore, training can be prescribed accordingly with the potential emphasis on particular drills for certain players, or additional top up conditioning to meet those specific intensities.

1.3 Purpose of the studies

<u>CHAPTER 3.</u> STUDY 1 – RELATIONSHIPS BETWEEN TRAINING MONITORING AND PLAYER MATCH PERFORMANCE IN PROFESSIONAL AUSTRALIAN FOOTBALL

- This study sought to determine the validity of characteristics for understanding player match performance from one AFL club standard monitoring process during the 2019 AFL season.
- The study also aimed to determine the relationship between coaches subjective ratings and Champion Data © player ratings.
- A practical aim of this work was the determination of whether any training monitoring tools are being collected unnecessarily by the club, as determined by their weak relationship with match performance.

<u>CHATPER 4.</u> STUDY 2 – PLAYER SPEED AND ACCELERATION VOLUME DISTRIBUTION WITHIN AN AUSTRALIAN FOOTBALL COMPETITION

- The purpose of this study was to determine the cumulative distribution of volume covered across the intensity spectrum for AF and examine the differences between level of competition (AFL vs VFL) and between match quarters (one - four).
- Overall, this study aimed to provide context around whether competition level and match quarter influence the distribution of speed and acceleration across matches and if so, what the differences are between the different conditions.

<u>CHAPTER 5.</u> STUDY 3 – SPEED AND ACCELERATION DISTRIBUTION ACROSS AN AFL PRE SEASON

- The purpose of this study was to determine the cumulative distribution of volume covered across the intensity spectrum for the different pre-season phases and training drill modalities in AF.
- Overall, the study aimed to provide further context around the differences if any in the speed and acceleration accumulated within the same training drill modality across different pre-season phases.
- Secondly, the study aimed to quantify the overall differences between each training drill modality and each pre-season phase.

<u>CHAPTER 6.</u> STUDY 4 – INVESTIGATING THE EFFECTS OF MATCH TURNAROUND ON SPEED AND ACCELERATION OVER AN ENTIRE AFL SEASON INVESTIGATING THE EFFECTS OF MATCH TURNAROUND TIMES

- The purpose of this study was to examine the cumulative distribution of volume during the different turnaround lengths for the 2022 AFL premiership home and away season.
- Secondly, the study aimed to further identify what stage of the training week accumulated the greatest volume and how the distribution of speed and acceleration alters between the two modalities.
- Thirdly, this study was trying to determine whether the accumulation of speed and acceleration alters in training sessions and matches when there is a different number of days between matches.

CHAPTER 2. REVIEW OF LITERATURE

2.1 Introduction to Australian Rules Football

Australian Rules football is an intermittent contact sport with multiple physical qualities alongside numerous technical elements i.e., handballing, kicking and tackling (Johnston et al., 2018). The highest level of AF is the AFL comprising 18 teams (Johnston et al., 2018). Australian football players need to demonstrate strength, agility, speed and have proficient muscular impulse and maximal aerobic power (Gabbett & Domrow, 2007). The total distance covered during a game by AF players has been reported in the literature as 12620 ± 1872 m at high intensities (129 ± 17 $m \cdot min^{-1}$), much greater than any other football code, as the total distance covered in Rugby League is reported as 6276 ± 1950 m and 10,274 ± 946 m in Soccer (Johnston et al., 2018; Varley et al., 2014). In AF, players typically cover 1322 ± 374 m of high-speed running (>5.5 $m \cdot s^{-1}$) (135.5 ± 3.85 $m \cdot min^{-1}$), with approximately two high speed running efforts (>3.9 $m \cdot s^{-1}$) per minute and 22 ± 9 sprint efforts (>7 $m \cdot s^{-1}$) on average per game (Johnston et al., 2018; Varley et al., 2014). The range of distance covered, high-speed running and sprint efforts are influenced by physiological capabilities and technical and tactical differences of each playing position (Gabbett, 2006a; Johnston et al., 2018; Varley et al., 2014). Australian football provides players with more freedom in their movement as dictated through the rules of the game, where other sports such as rugby have to follow a more strategic structure given the rule of offside, and netball where players are restricted to different areas of the court based on their position (McIntosh et al., 2018a). This freedom in field movement allows players to perform multiple roles across the field, however they are still typically classified in a predominant playing position (Gallo et al., 2015).

2.2 Activity Profile of Australian Rules Football

In AF, each playing position has different physical and technical traits (Gallo et al., 2015). An example of the on-field positions and the positional set up can be seen in Figure 2-1. Further the half-forward flank and half-back flank are classified as small forwards and small backs, respectively, forward pocket and back pocket are classified as full/key forwards and key/full backs, respectively and lastly, wing, centre, ruck rover and rover are classified as midfielders, where all other positions listed have no classification difference (Brewer et al., 2010; Johnston et al., 2018). These classifications can be split into two main groups being nomadic (midfielders, small forwards and small defenders) and fixed position players (key forwards and backs, ruck and centre half positions) (Brewer et al., 2010).

There are multiple variables or conditions that can influence the metrics observed within matches and training, consisting of playing position (Brewer et al., 2010; Johnston et al., 2018), competition level (Brewer et al., 2010), stage of the match (Mooney et al., 2013), stage of the season (Moreira et al., 2015; Ritchie et al., 2016) and also match turnaround lengths (Cormack et al., 2008; Esmaeili et al., 2018; Ryan et al., 2017). Therefore, the metrics recorded such as total distance, high speed distance, accelerations, decelerations and maximal speeds, are highly dependents on the contextual factors and will vary making it harder to determine a definitive number for what metrics an AF match produces.

Within matches typically, nomadic players cover the greatest total distance (midfielders; 12637 ± 1637 m and small forward/back; 12963 ± 1575 m) and high-speed efforts (midfielders; 295 ± 51 and small forward/back; 292 ± 45) with centre half forwards/backs achieving the fastest velocity (29.6 ± 1.1 km·min^{-1} (Brewer et al., 2010). Fixed position players typically have the lowest work rate (full forward/backs; 119 ± 17 m·min^{-1}, centre half forwards/backs; 120 ± 10 m·min^{-1} and rucks; 123 ± 9 m·min^{-1}) compared to nomadics (midfielders; 135 ± 12 m·min^{-1}, small forwards/backs; 127 ± 9 m·min^{-1}; (Brewer et al., 2010), however, fixed position players perform the most accelerations and decelerations due to the nature of their position (Johnston et al., 2015b). Throughout the duration of a match total distance has been shown to reduce likely suspected from the effects of fatigue (Coutts et al., 2010; Wisbey et al., 2010) however, other research has identified consistency between total volume across the match resultant from the high conditioning level of the players at the elite level (Aughey, 2010). Suggesting that further research is required in this area investigating the effect of duration in the match on match variables and also whether this difference is evident across difference competition levels as well.

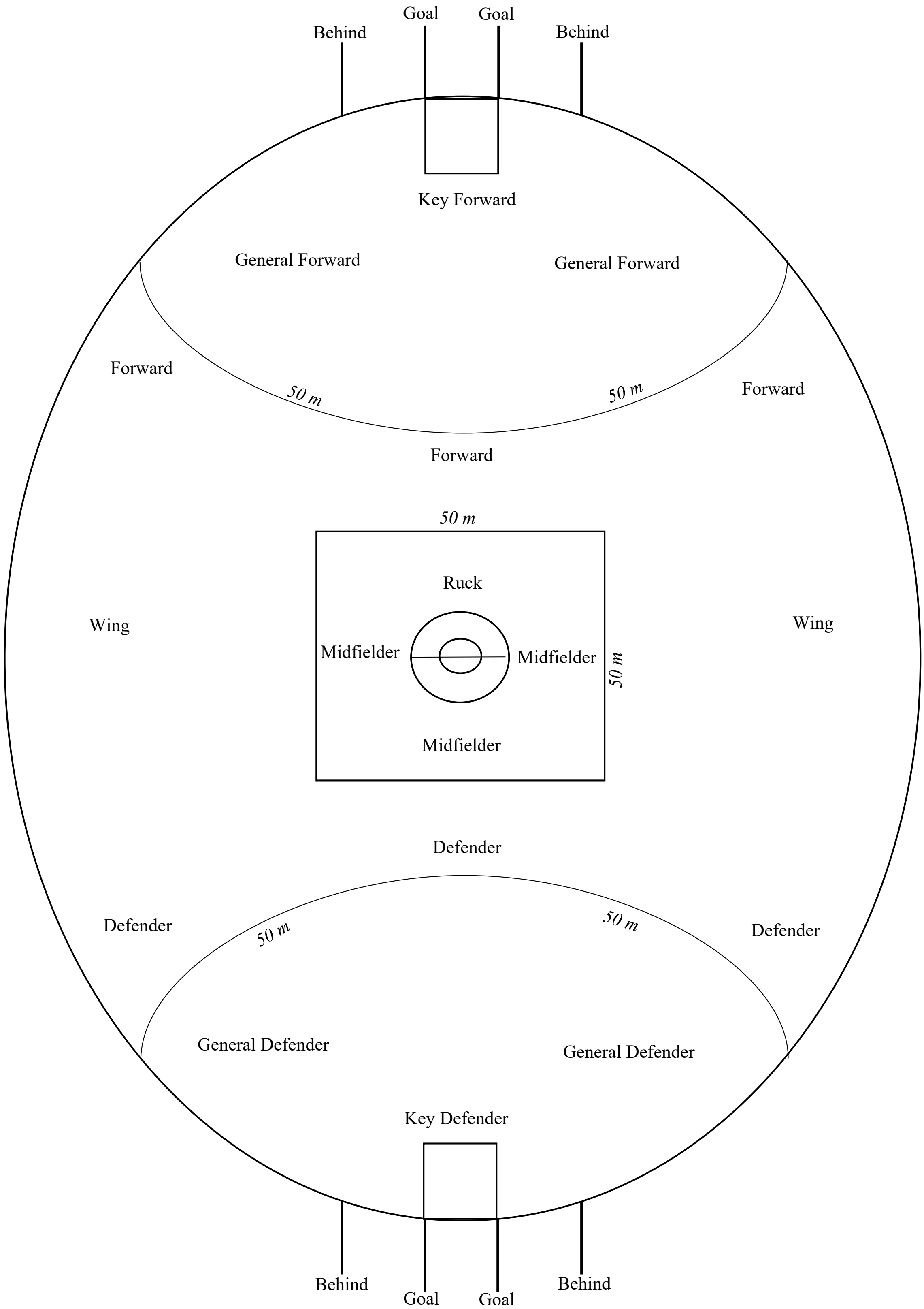

Figure 2–1 Overview of the playing positions and field set up in AF. Adapted from (Johnston et al., 2018).

As well as differences within positions and match duration, there are differences between the various levels of AF, being the elite level (AFL) and sub-elite, such as VFL or other state leagues. The total distance accumulated throughout matches is seen to be higher at the sub-elite level (12502 ± 1889 m) compared to elite (12311 ± 1729 m), however, the elite level demonstrates greater movement demands overall compared to sub-elite identifying the elite level as higher intensity (Brewer et al., 2010). More recent research into AF has reported one minute maximal mean speeds achieved in matches at the elite level of 199 – 222 $m \cdot min^{-1}$ (Delaney et al., 2017) supporting this notion of a higher intensity match experience in elite compared to sub-elite levels.

Differences in total distance and intensity are also observed at different stages of the season, where the season can be broken down into two overruling phases, being pre-season and in season. The pre-season phase can further be broken down into three smaller phases, or mesocycles, where there is a different focus in each phase that is periodised into players training programs (Bompa & Haff, 2009; Moreira et al., 2015; Ritchie et al., 2016). Typically training sessions during the first pre-season phase sees players accumulate a large amount of distance often at lower intensity (20000 ± 8200 m, 99 ± 201 $m \cdot min^{-1}$), where players are trying to develop their aerobic base and improve overall fitness conditioning (Farrow et al., 2008; Moreira et al., 2015; Ritchie et al., 2016). During the second pre-season phase, training sessions tend to increase in volume and intensity (21400 ± 7300 m, 101 ± 152 $m \cdot min^{-1}$) (Ritchie et al., 2016) as there is an increased importance in drill prescription that simulate or exceed match intensity incorporating both technical and tactical components. The last phase of the pre-season is when players are playing in practice matches which is preparing them for the preceding competition season where training volume is often reduced through both distance and intensity (10200 ± 5600 m, 98 ± 149 $m \cdot min^{-1}$) , as the practice matches provide high intensity exposure throughout this phase (142 ± 73 $m \cdot min^{-1}$) (Ritchie et al., 2016). The final pre-season phase also provides players with the opportunity to rest and recover to best position themselves for the competitive season where there is often a focus on recovery and rejuvenation (Slattery et al., 2012).

During the in season phase, training loads are relatively well maintained and comparative to those of the third phase of pre-season, as matches are now the key contributor to players overall training load, where players accumulate the greatest distance and intensity for the week (13,300 – 13,500 ± 1700 m, 132 – 133 ± 57 – 80 $m \cdot min^{-1}$) (Ritchie et al., 2016). Despite the well reported differences between different stages of the season, it is still underreported as to the differences between different types of training drills prescribed through said phases. Understanding the differences between various training drills can provide further context for practitioners to reference to in their training drill prescription. Often in the literature training drills are broken into warm up, skills, conditioning, small sided games and match simulation (Ritchie et al., 2016), however, no further analysis is reported within the skills category. Research published in 2017 provides a great example of how there are numerous skill based drills designed and implemented within an AF club (Corbett et al., 2017), where this particular research investigated 35 different training drills consisting of small sided games with various conditions (i.e., field size, players, area of the ground), skills based drills (i.e., tackling, kicking or handballing focused) and various defensive or attacking style drills. The investigation conducted by Corbett et al. (2017) however, was seeking comparison between performance in matches and training rather than quantifying the differences of how training volume is accumulated through different drills.

Another underreported comparison in the literature is the difference in training load accumulated when there are a different number of days between matches during the competitive season i.e., between match turnaround length. In AF the season is designed where teams play one match per week on a day allocated in the fixture where the between match turnaround length can vary every week (Moreira et al., 2015). Following the model of periodisation, training volume and intensity are manipulated based on the between match turnaround length for each given week. Regardless of the length of the turnaround, matches always accumulate the greatest distance and intensity throughout the week when compared to training, likely resultant from the difficulties of replicating match demands in training (Corbett et al., 2017; Gabbett & Mulvey, 2008) and the periodisation model in which training loads need to be carefully monitored throughout the week. Training volume is often reduced during short (<6 days) and long (>12 days) turn around lengths, as seen through a reduction in total distance accumulated (Esmaeili et al., 2020; Ryan et al., 2017). This reduction in distance can be attributed to a decreased opportunity for players to train (Ryan et al., 2017), whereby shorter turnarounds do not provide enough days to allow recovery and multiple training sessions on top, given it takes players four days to recover post-match (Cormack et al., 2008). The differences in total volume across varying between match turnaround lengths have been minimally reported in the literature, however, no further investigations have elaborated on these findings to provide more context around the accumulation of speed and acceleration across varying intensity and whether the same accumulation is evident in matches when there has been a different number of days between matches.

Australian Football players need to be a well-rounded athlete with strong tactical and technical skills to provide the environment for players to best perform (Coutts et al., 2010; Gray & Jenkins, 2010; Heasman et al., 2008; Johnston et al., 2018; Robertson et al., 2016; Sullivan et al., 2014). Despite these quantifiable differences in matches, coaches perceptions have been reported as being influenced from a players skill involvement more so than their physical work rate (Sullivan et al., 2014) and nomadic players often have the most skill involvements per minute, 0.17 ± 0.06 (Hiscock et al., 2012). Skill involvements have shown to have a small correlation to movement variables such as total distance (m) and work rate ($m \cdot min^{-1}$) (ES = 0.1 ± 0.01) (Mooney et al., 2011), but a moderate correlation with high intensity running ($m \cdot min^{-1}$) ($r = 0.28$, $p<0.001$) (Hiscock et al., 2012). As skill involvement is a poor indicator of match performance (Heasman et al., 2008; Johnston et al., 2012), Champion Data © rating points can instead be used as a performance indicator (Hiscock et al., 2012; McIntosh et al., 2018b; Mooney et al., 2011), which will be further discussed in section 2.6.1.1.

Players respond differently to training, which can also fluctuate day to day and between modalities, resultant from individual differences (Mann et al., 2014; Vollaard et al., 2009). There are known differences in load tolerance and injury risks between players which may have some correlation to positional differences, however, there is no conclusive evidence to support what the physiological differences are that result in said variances. It is not as simple as categorising players responses based on their playing position as not all players from the same positional group respond the same way (McIntosh et al., 2018a). Research has been conducted in AF to determine similarities and dissimilarities between playing positions to classify players into *a priori* determined player role categories and to identify the closeness of playing style between individuals (McIntosh et al., 2018a). Figure 2-2 displays the descriptive statistics of the relative contributions from each of the AFL Player Rating categories identified by Champion Data©, by each player role classification across the 2016 season adapted from McIntosh et al. (2018a). It can be seen in Figure 2-2, key defenders and general defenders receive the greatest involvements regarding intercepts, where ruck, midfield, midfield-forward and general forwards have a larger diversity in their skill involvements and lastly, key forwards have their greatest skill involvements from mid-chain (McIntosh et al., 2018a). Mid-chain involvements as classified by Champion Data© are classified as points gained through possessions at stoppages or as intercepts (Champion Data Pty Ltd., Melbourne, Australia), which are further elaborated on in Table 2-4, as part of section 2.6.1.1. These differences observed in Figure 2-2, were not investigated as to why these differences existed as the reasoning behind why players respond to training differently is attributed to the individual. To create tailored training for players, sport specific demands and their individual responses, it is crucial to follow basic training principles in the program design which will be explained further in the following section.

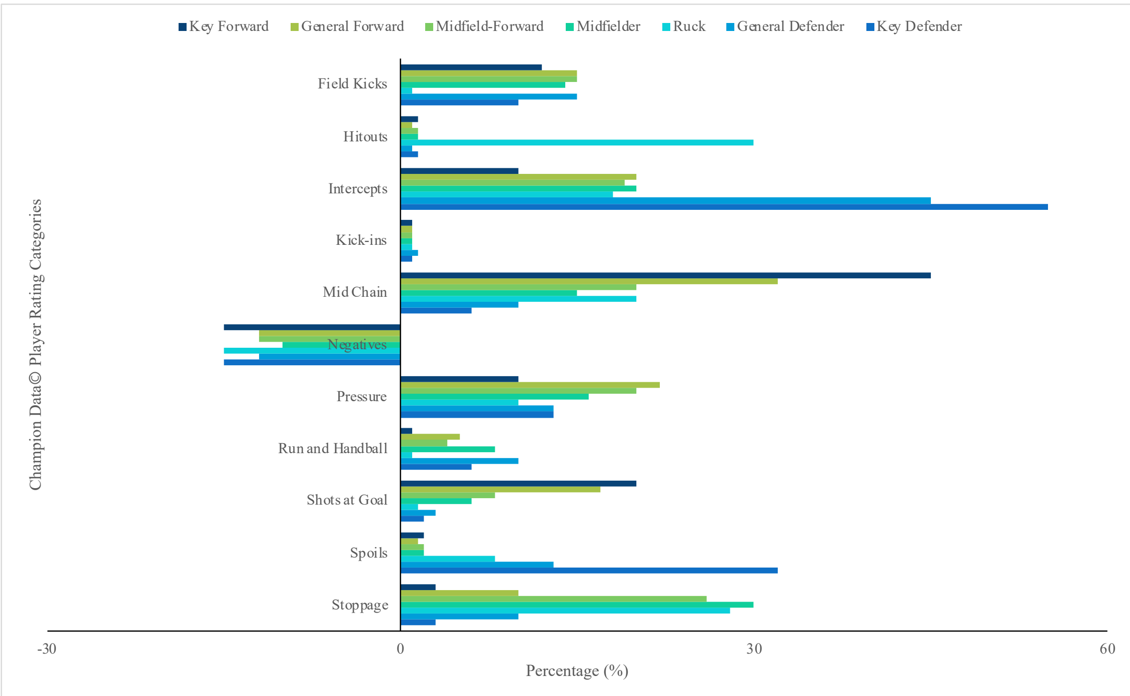

Figure 2–2 Descriptive statistics of the relative contributions from each of the AFL Player Rating categories identified by Champion Data©, by each player role classification across the 2016 season adapted from McIntosh et al. (2018a).

2.3 Training Process in Football

2.3.1 Training Principles

Training is the process of preparing athletes for performance in a physical, tactical, technical, and psychological sense (Bompa & Haff, 2009; Lambert et al., 2008). The goal of training is to improve performance (Banister et al., 1991), where physical performance can be quantified as a result of fitness minus fatigue, a point that will be further explained in section 2.8.1. Achieving peak performance is still an area being explored as there is no guaranteed method that will produce peak performance given every sport is different (Lambert et al., 2008).

Each training session induces a myriad of acute responses through physiological stress, which if continued have the potential to create chronic adaptations (Brooks et al., 2005; Coyle, 2000). Physiological stressors include but are not limited to; increased heart rate, increased oxygen uptake, increased oxygen consumption, increased body and muscle temperature, increased respiration, increased perspiration, heightened stress hormones and movement specific muscle recruitment (Brooks et al., 2005). The type and effect these training adaptations have on athletes are dependent on the training stimulus, determined by the prescription of training (Brooks et al., 2005; Coyle, 2000). Training stimuli includes variables such as; mode; the type of training session i.e. swimming, running, kicking drills, match simulation, intensity; how hard the training session is, duration; how long the training sessions runs for and frequency; how often the training sessions is completed.

Training adaptations are designed and implemented as a means of enhancing performance and reducing the risk of injury (Lambert et al., 2008). There is a fine line with training prescription where, too little exposure to physiological stressors do not induce adequate adaptations or too much stress causes maladaptations, where both scenarios result in suboptimal performance (Budgett, 1990; Derman et al., 1997). To best prepare athletes to achieve peak performance, multiple fitness components need to be trained or monitored to best understand athletes and prepare competitions or performances. In AF the key physical attributes are known to include; aerobic fitness, speed, agility, strength, power and body composition (Johnston et al., 2018). Training sessions needs to consider these fitness components within the design and can be manipulated to suit the needs of the athlete or team, sport, and the phase of training. In AF, aerobic fitness (Bellenger et al., 2015; Buchheit & Laursen, 2013; Lorenzen et al., 2009), speed (Johnston et al., 2018) and agility (Johnston et al., 2018; Pyne et al., 2005) can all be targeted in different drills throughout training, where body composition can be targeted through off-field gym based training (McGuigan et al., 2006; McGuigan et al., 2012) and nutritional education (Sánchez-Díaz et al., 2020). To effectively design training there are six basic principles that need to be considered; specificity, individuality, overload, maintenance, reversibility, and periodisation which will further be explained following.

2.3.2 Specificity

In a training sense, specificity refers to adaptations being dependent on the type of training stress, where the greatest increases in performance are resultant when the physical and movement demands in training mimicking those in a match/performance for each individual (Rushall, 1990). However, if you simply program every training session to replicate match performance this can lead to greater susceptibility to injury or overtraining for athletes, dependent on the intensity of the relevant movement demands from their sport (Young, 2006). Training needs to be a programmed trade-off between exposing athletes to match/performance intensity and training load to induce sufficient physiological stressors whilst also providing the necessary time for recovery and technical and tactical development. The principle of specificity not only relates to the mode of training i.e., running, swimming, strength sessions, but also the muscle groups targeted and energy systems trained (Birch et al., 2005).

Team sports pose a challenge for coaches to make training specific to their athletes because they typically train together (Los Arcos et al., 2015). As previously mentioned in section 2.2, athletes respond differently from the same stimulus (McIntosh et al., 2018a), therefore, athletes might perform a similar amount of physical work (external training load) however, it will elicit different responses internally (Halson, 2014). Emphasising the importance for practitioners to design training incorporating physical and tactical components targeted to replicate match demands to best position athletes to improve their performance (Corbett et al., 2017), which will be further discussed in section 2.4.1.1. It is understood training specificity is important for performance, but it is also crucial for training to be specific to the individual as everyone responds in a different way leading to the next principle of individuality.

2.3.3 Individuality

An individual's response to training is a process unique to that particular individual as no one will respond in exactly the same way (Bourdon et al., 2017). For example, a player's ability to tolerate the physical and psychological work they are completing (load tolerance), susceptibility to injury, physiological and psychological changes and body composition all vary (Halson, 2014). These varied responses between individuals are commonly attributed to hereditary differences (Bouchard et al., 1999) including; cell growth and repair, metabolism and nerve and hormone regulation (Birch et al., 2005), but these can be influenced by behavioural and environmental factors such as sleep (Kentta & Hassmen, 1998), nutrition (Hawley et al., 2011) and recovery (Stanley et al., 2013). Inter-individual differences are commonly reported in the literature, for example, resting heart rate (Scharhag-Rosenberger et al., 2012), heart rate variability (Aubert et al., 2003), maximal oxygen uptake (Scharhag-Rosenberger et al., 2012; Vollaard et al., 2009), exercise systolic blood pressure (Bouchard & Rankinen, 2001), aerobic threshold (Prud'homme et al., 1984) and anaerobic threshold (Scharhag-Rosenberger et al., 2012).

Individual variation can produce a myriad of responses where an athlete may be a low responder to one training response, but this does not mean they will be a low responder across all training responses (Mann et al., 2014; Vollaard et al., 2009). Training responses were originally studied by comparing the mean differences between athletes (Bouchard, 1983), however, this did not accurately reflect athletes who may have been high responders for some responses and not others as only a mean score was analysed. The concept of training monitoring has vastly improved with the advancements of technology available and increasing involvement from practitioners, increasing the capability to accurately measure training responses which will be further discussed in sections 2.4 and 2.5.

2.3.4 Overload

The principle of overload is the systematic approach of exposing athletes to new stressors at regular intervals exceeding the previous stress to induce new adaptations (Lambert et al., 2008). Too little or too much physiological stress can result in suboptimal performance, therefore it is important that the new stressors are introduced at an appropriate time to provide an ideal environment for the athletes to adapt. The process of overload starts by imposing a physiological stress on an athlete, initiating a homeostatic reaction causing physiological and metabolic changes, returning the body to normal resting levels which if continued over time will cause the "baseline" to then shift to a level that was previously a stressor (Birch et al., 2005; Coyle, 2000; Lambert et al., 2008). For example, an athlete completing a bicep curl for eight repetitions with 12 kg, initially the body will respond to this as a stressor but after a time interval in which this exercise has been repeated, the exercise will become easier and eight repetitions with 12 kg will become the new baseline for which overload can be applied through manipulating various principles.

To manipulate the stress, overload can be imposed through changes in frequency, duration, intensity, and recovery (Bompa & Haff, 2009). Frequency and duration refer to the amount of sessions per week, cycle or even day and the total time taken for a training session, respectively (Lambert et al., 2008). Intensity is more complex as there are multiple ways to manipulate intensity within a training session which generate the greatest adaptations in players directly influencing their performance capacity (Lambert et al., 2008). Table 2-1 shows a list of some alterations that can be incorporated into AF training sessions to manipulate the intensity.

The final umbrella category to manipulate stress is recovery, referring to the time between training sessions, and more specifically between exercises or repetitions. Recovery can be altered through changing the rest time between 20 m sprint efforts in on field training or between exercises in a gym session. Although often neglected (Lambert et al., 2008), recovery can be argued as the most valuable principle as it controls whether physiological stress induces adaptations or maladaptations. Referring to the example earlier with the bicep curl, taking into consideration these principles, to overload the athlete completing 8 repetitions of 12 kg, you could either increase the weight to 14 kg, decrease the rest time between sets or increase the frequency you complete the exercise to name a few possibilities. As mentioned, elite athletes adapt at slower rates as they are already exposed to such high training stimuli, therefore it can take a week if not longer before a 1% increase can be achieved emphasising the need to overload slowly and cautiously in elite populations (Birch et al., 2005).

Table 2–1 Examples of intensity manipulation in AF training sessions

Type of training session	*Intensity manipulation*
Gym sessions	• Machine weights vs free weights • Changing the exercise order • Single limb vs multi limb exercises • Speed of exercises • Varying the amount of repitions
On-field sessions	• Setting target times for various drills i.e. 20 m sprints under 3 seconds, 4 seconds and 5 seconds • Increasing the pressure in match simulations • Incorporating decision making components into running drills • Reducing the size area a drill is completed in i.e. 3 v 3 handball drill in a 20 m² area, then reduce the size to 10 m²

2.3.5 Maintenance

The principle of maintenance refers to when athletes have developed the desired level of adaptation for that component and the goal is to maintain this level without necessarily increasing it (Birch et al., 2005). In saying this, to continue to maintain the achieved adaptation level, targeted training must continue, however, it may reduce in frequency i.e., pre-season was four long distance running sessions targeted at cardiovascular fitness but in season you only complete two long distance sessions.

It is unlikely a coach/practitioner is able to program every single fitness component with equal importance across a week for maximal improvements so it is common to target one or two key components while maintaining the remainder for a period of time then shifting to target the next desired area (Birch et al., 2005). In a soccer pre-season training was targeted at aerobic fitness and strength and as the season approached, the training shifted to a focus on speed and power (Birch et al., 2005). A similar pattern can be seen in AF as it is common for pre-season training to focus on fitness and large strength gains and as the competitive season nears, training shifts focus to more high-speed efforts and match simulation with strength focused on power and maintenance (McGuigan et al., 2009; Moreira et al., 2015; Ritchie et al., 2016). All fitness components in AF are important to varying degrees, however, different levels of importance are inherently placed on each component and training reflects this in the different phases (Johnston et al., 2018; Young et al., 2005).

2.3.6 Reversibility

Regular training exposing athletes to physiological stressors prevents the homeostatic reaction to reset to baseline levels closer to pre-training levels, where the longer the period without training, the further the baselines regress (Birch et al., 2005; Mujika et al., 2004). This effect can be described as “detraining” where the adaptations gained through training are overturned, directly reducing performance at both the maximal and submaximal level (Birch et al., 2005). Due to the high levels of training elite athletes complete, the effect of detraining takes longer to cause a negative effect when compared to an active adult from a general population (Birch et al., 2005). Detraining over a period as long as four weeks in elite athletes caused significant decreases in muscle strength (Mujika & Padilla, 2000), physiological capacity i.e., oxygen uptake, stroke volume, cardiac output (Mujika & Padilla, 2001) and effect proprioception (Kouzaki et al., 2007). These reversed maladaptations are commonly caused in the elite population through injury, competition schedule, retirement or season intervals (Dai et al., 2012).

Four weeks of missed or insufficient training has a known significant effect on training adaptations (Mujika & Padilla, 2000), emphasising the detrimental effect of an injury, which in turn would result in a longer period of reversibility determined by the dynamics of the injury. Injuries cannot be avoided but they can be accounted for once they occur. It is important for practitioners around elite athletes to develop targeted and specific management programs to optimise athlete's recovery to reduce the effects of detraining as much as feasible.

2.4 Training Design in Football

2.4.1 Periodisation

Training prescription traditionally, has followed the model of periodisation, a concept where coaches divide a time continuum into manageable time frames with individualised goals (Bompa & Haff, 2009). The training prescribed within each time frame is manipulated through load, volume, and intensity (Bompa & Haff, 2009; deCunanan et al., 2018; Mujika et al., 2018). The training phases prescribed by coaches can be split into two overruling phases; preparation and competition, which can further be broken down into; general preparation, specific preparation, precompetitive, main competition and the taper (Bompa & Haff, 2009). The training load, volume and intensity can all be monitored through appropriate training monitoring techniques which will be further elaborated on in section 2.5.

2.4.1.1 Training Mesocycles during a Football Season

During a football season there are only two phases of training; pre-season and in-season (Moreira et al., 2015). Then within these two overruling phases, there are numerous mesocycles which are a typical duration of four to six weeks, where there is a key focus within each mesocycle (Bompa & Haff, 2009; Moreira et al., 2015; Ritchie et al., 2016).

2.4.1.2 Pre-season vs In-season

In football, pre-season is the phase in which there are high training loads with an emphasis on increasing the physiological demands placed on athletes (Gabbett & Domrow, 2007). The pre-season phase in AF specifically, can be broken down into three different mesocycles associated with the time period of pre-Christmas, post-Christmas and pre-competition (Buchheit et al., 2015; Ritchie et al., 2016). Alternatively, the in-season phase has a more varied structure in which the number of mesocycles can vary dependent on how far a team makes it through the season i.e. making the finals series or finishing at the end of the home and away season. A study in sub-elite rugby players showed training load to be greatest during the pre-season, with reductions in the pre-competition phase and reducing as the season continued (Gabbett & Domrow, 2007). Supported by research conducted in AF, where there were 20,448 individual training sessions reported across a season with 10,956 in the pre-season and 9,492 in-season (Moreira et al., 2015).

The clear difference between pre-season and in-season is the presence of matches, where pre-season only comprises training sessions, where in-season comprises both training and matches. This directly alters the overruling aim between phases, where in-season is centralised around recovering between matches and allowing for optimum performance (Moreira et al., 2015; Slattery et al., 2012). Matches accumulate the greatest training load within the training week (shown in Figure 2-3) as they are the most demanding task from the week (Los Arcos et al., 2017; Moreira et al., 2015). As seen in Figure 2-2, all training session types excluding matches show a reduction in training load in the in-season phase, providing the room for the increased training load accumulated through matches, following the training principles aforementioned in section 2.3. By reducing the training load accumulated in other training sessions, this lessens the risk of overload, given the greater training load accumulated through matches.

Another variable that changes between the two phases, is training intensity which is shown to increase during the in-season phase. Table 2-2 displays data collected from different football codes and the differences between the proportion of high intensity sessions per week pre-season compared with in-season. Moreira et al. (2015) defined high intensity sessions as those rated greater than seven using the Borg CR-10 RPE scale, whereby Algroy et al. (2011) utilised a 10 point session RPE scale, where greater than seven was categorised as high intensity sessions. With increasing intensity and training load accumulation is the increased emphasis and importance for recovery and accurate training monitoring protocols in place to be able to accurately track athletes during their training (Moreira et al., 2015).

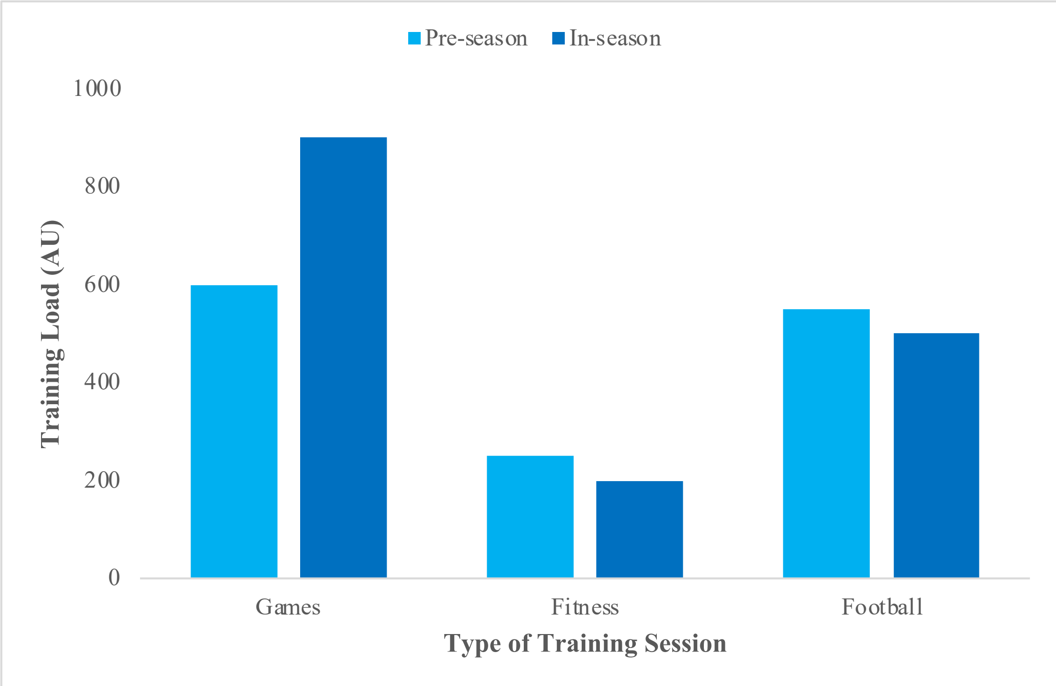

Figure 2–3 Training load (arbitrary units) for each type of training session across pre-season and in-season phases in AF adapted from (Moreira et al., 2015).

Table 2–2 Training Intensity as reflected through the distribution of high intensity training sessions from the training week across different football codes.

Training Intensity (number of high-intensity sessions)		*Sport*	*Reference*
Pre-season	*In-season*		
18.1%	22.7%	AF	(Moreira et al., 2015)
27±4%	38±6%	Soccer	(Algroy et al., 2011)

2.4.1.3 Intra-phase training session modalities

Matches are known to accumulate the greatest training load per week during in-season, however, changes in training load between different training session modalities excluding matches is less reported. Literature appears to report findings using modalities such as; skills (Corbett et al., 2017; Farrow et al., 2008; Moreira et al., 2015; Ritchie et al., 2016; Thornton et al., 2020), weights/resistance training (Ritchie et al., 2016), other (Moreira et al., 2015; Ritchie et al., 2016) and running/conditioning (Corbett et al., 2017; Moreira et al., 2015; Ritchie et al., 2016; Thornton et al., 2020). Other is a category that comprises any off field conditioning or rehabilitation sessions which can include modalities such as; boxing, cycling, swimming, cross-training, balance, pilates or hydrotherapy (Moreira et al., 2015; Ritchie et al., 2016).

When analysing training session modalities, excluding matches, skills and running sessions accumulate the greatest training load throughout pre-season (Moreira et al., 2015; Ritchie et al., 2016; Thornton et al., 2020). Understandable given the overruling aim of pre-season being to increase the physiological demands placed on athletes (Gabbett & Domrow, 2007), where it is known the best training prescription to elicit performance gains, is through replicating match demands in training (Barris et al., 2013; Pinder et al., 2011). It has become common practice within training prescription to include match simulation drills, often in the form of small sided games to try and expose athletes to said demands before their exposure to matches (Barris et al., 2013; Pinder et al., 2011).

2.4.1.4 Replicating Match Demands – The use of Small Sided Games

Small sided games (SSG), using reduced field sizes or reduced players have become the norm for most elite sporting clubs and are one of the most common drills used in football (Hill-Haas et al., 2011). Small sided games are designed to incorporate match performance into a training setting aiming to target the technical and tactical strategies of the game whilst simultaneously improving physical fitness (Hill-Haas et al., 2011). It has become common practice in AF training sessions to incorporate SSG and larger match simulation drills, however there are limitations associated with training given the difficulties in replicating match demands (Corbett et al., 2017; Gabbett & Mulvey, 2008).

Physiological changes have been identified that confirm athletes are capable of working at a high intensity during SSG through measures of lactate concentration and heart rate (Halouani et al., 2014), reflecting a change in physiological capacity. However, these responses are heavily dependent on the training conditions where changes in pitch size, players on field, duration of the game or any other changeable factor can have a considerable effect on the intensity of the SSG (Halouani et al., 2014).

These simulation drills fail to provide the same environment, which has been quantified through less kicks under pressure and fewer kicks being completed in under two seconds (Corbett et al., 2017). This can be explained through the dynamic nature of AF (Appleby & Dawson, 2002) comprising both technical and tactical capacities (Corbett et al., 2017). With any motor skill, regardless of the sport there are three inter-related constraints that can affect our ability to perform said skill, being related to the individual, environment or task/performance environment (Magill, 2021). A model originally created by Newell (1986), termed "Newell's model of constraints", has now been adapted more recently in a sporting context by Magill (2021). In AF specifically, examples of these constraints can be anthropometric variables such as height and weight or physiological capacity for the individual, external pressure from opposing players or teammates for environment and lastly, rules of the games or requirements within a drill for the task (Corbett et al., 2017). Constraints although individual and from different areas, are all heavily influential over consequential responses, making it extremely challenging for practitioners to replicate match demands in training, as matches appear to always accumulate more training load (Corbett et al., 2017; Gabbett & Mulvey, 2008; Moreira et al., 2015; Ritchie et al., 2016).

2.5 Training Load

Training load is a function of volume and intensity and can be considered as the actual work completed (external load) and how an athlete responds to that work (internal load) (Bourdon et al., 2017; Halson, 2014). To adapt to training you must place the body under stress and in doing so expose athletes to moderate to high training loads, however, this has the potential for negative side effects such as fatigue, illness or injury (Gabbett, 2016; Halson, 2014; McLaren et al., 2018). The relationship between stress and fatigue can be described as a "training-injury paradox" (Gabbett, 2016) in which there is a trade-off between training too low or high and injuries (Figure 2-4). There is no one definitive measure for training load that can be used, instead measures need to be considered through a combination of monitoring tools reflective of the sport including the individual circumstances of the athletes within a team (Halson, 2014). The trade-off between load and injuries emphasises the importance of monitoring training load to aid in reducing the risk of illness and injuries as much as possible for what is within control. Training load monitoring is a concurrent measure of physiological and psychological stress. It has become common practice in elite team sport as its quantification can assist coaches and support staff providing information relevant to an athlete's readiness to train (Bourdon et al., 2017; Buchheit, 2014; Myers et al., 2017).

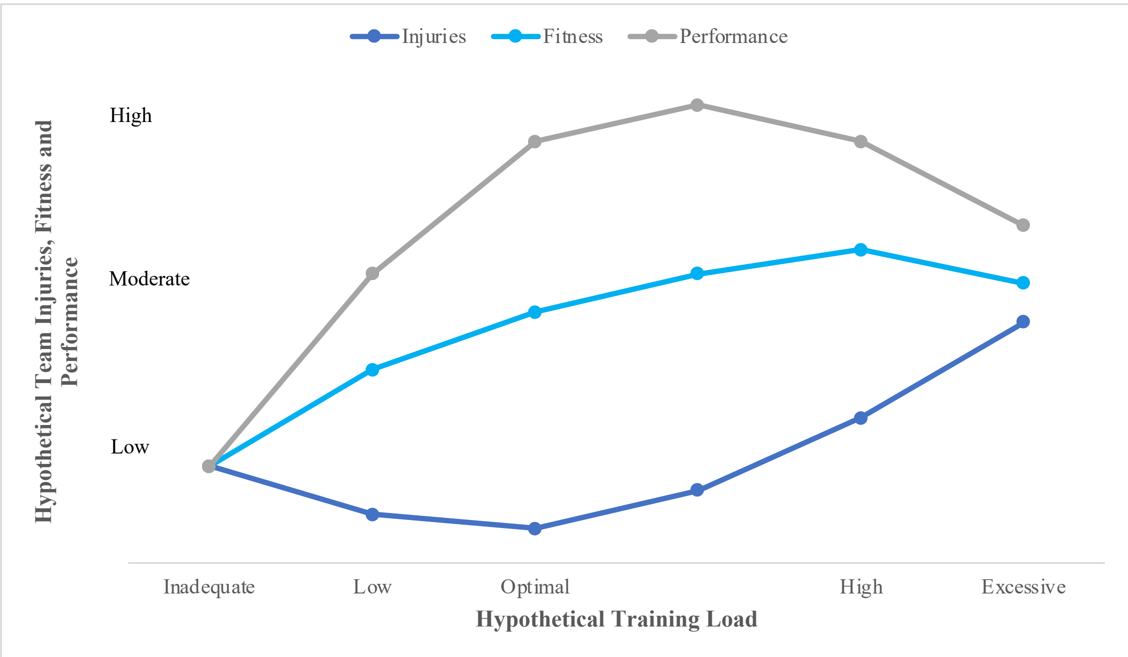

Figure 2–4 Training-injury paradox adapted from (Gabbett, 2016) redrawn from (Orchard, 2012).

2.5.1 Measurement systems for External Load

External training load is the actual work completed by the individual that can be measured through various monitoring tools (Halson, 2014). External training load can largely influence an individual's internal training load as it can be expected, the harder you train, the more fatigued you feel, given the physical amount of work you do has a high correlation with how you subjectively feel (Halson, 2014). In team sports, the monitoring tools focused on are those that quantify variables such as speed, acceleration, power, and distance covered. Global Navigation Satellite Systems (GNSS) are the norm in AFL clubs now as they provide real time data of the athletes movement demands during trainings and matches (Gray & Jenkins, 2010). This technology allows measurement of athlete movement patterns, through measuring variables such as total distance, high speed running, accelerations and decelerations (Rampinini et al., 2015; Varley et al., 2012b).

The analysis of movement patterns provide an indication to how the athlete is performing, responding to training stimuli and adherence to prescribed training intensity and training load (Cummins et al., 2013). Global Navigation Satellite Systems are a reliable and valid training monitoring tool, where extensive reliability and validation studies have been conducted, most notably the studies conducted through FIFA's Quality Performance Reports for Electronic Performance Tracking Systems (Retrieved July 2, 2023, from https://www.fifa.com/technical/football-technology/standards/epts/fifa-quality-performance-reports-for-epts). According to the most recent testing conducted on the various tracking technology systems, Catapult Sports (Victoria, Australia, Vector S7 units) meet the international match standards criteria and are rated highly for accuracy and consistency. Alternate options for player tracking include local positioning systems (LPS) and also optical tracking. Local positioning systems collect the same type of data as GNSS, however, it is collected through locally installed short-range signalling beacons and optical tracking is where athletes are tracked real-time through reflection markers followed through one to multiple camera systems.

2.5.1.1 Athlete Tracking Systems

Tracking athletes allow practitioners to know an athlete's position, displacement, velocity and acceleration which is of utmost importance to training prescription and load monitoring (Aughey, 2011). Athlete tracking is a useful tool given the units have the ability to provide quantified real-time feedback to aid in training load prescription and match day decisions (Torres-Ronda et al., 2022; Vanrenterghem et al., 2017). Various modalities for athlete tracking exist, including time-motion analysis, semi-automatic tracking and wearable sensors, which includes, accelerometers, GNSS and LPS.

Accelerometers report on the frequency and magnitude of movement in the three dimensions, medio-lateral, anterior-posterior and longitudinal planes (Boyd et al., 2013). Global navigation satellite systems provide location information through time signals sent to satellites orbiting the earth (Larsson, 2003) from which athletes' movements can be derived, where LPS track the same movements through time signals sent to an antenna located near the data collection area (Aughey, 2011). Accelerometers can also be incorporated inside GNSS units which has been reported in the literature through Boyd et al. (2013).

Given the vast amount of tracking technologies and products, it is crucial that practitioners utilise technologies and make decisions regarding data collection and analysis that are both specific to the sport and the environment in which data collection is taken (Torres-Ronda & Schelling, 2017). Investigating these technologies in AF specifically, GNSS systems are used competition wide, where LPS systems are used when matches are played at indoor stadiums (n=1 indoor stadia). Further explanation and application of the different tracking systems will be explained in the following sections.

2.5.1.2 Accelerometers

Accelerometers are a small, lightweight unit that can measure movement across the three different dimensions which are termed medio-lateral, anterior-posterior and longitudinal planes (Boyd et al., 2013). Accelerometers sample at a high frequency, 100 Hz, and have been used to quantify the external load in team sports, specifically, rugby league (Cunniffe et al., 2009; Fox et al., 2020; Gabbett, 2015), team sport training (Wundersitz et al., 2015), netball (Cormack et al., 2014) and AF (Boyd et al., 2013).

Using accelerometers provides practitioners with more data and information around motion, more specifically acceleration, where the key variable of interest is PlayerLoad™ (Boyd et al., 2011; Boyd et al., 2013; Cormack et al., 2013; Scott et al., 2013). PlayerLoad™ is a measure that identifies external load for an individual and can quantify this load in elite team-sports (Montgomery et al., 2010). PlayerLoad™ is calculated through an equation (Figure 2-5) comprising the instantaneous rate of acceleration in all three dimensions relative to the sampling frequency of the unit itself and is expressed in arbitrary units (AU).

$$PL = \sqrt{\frac{\left(a_{y1} - a_{y-1}\right)^2 + \left(a_{x1} - a_{x-1}\right)^2 + \left(a_{z1} - a_{z-1}\right)^2}{100}}$$

Figure 2–5 PlayerLoad™ equation taken from Bredt et al. (2020).

The data derived from accelerometers is able to inform practitioners about differences in PlayerLoad™ between different playing positions, competition levels and different modalities i.e. training vs matches (Boyd et al., 2013) for AF, as well as collision information for rugby (Gabbett et al., 2010). It has been reported that midfielders have a higher PlayerLoad™ compared to nomadics and deeps, where deep players are key position players who are located mostly in either the attacking or defending areas of the ground (Boyd et al., 2013). Comparing between competition levels has shown that elite midfielders, nomadics and ruckmen all accumulate higher PlayerLoad™ compared to their sub-elite positional equivalent (Boyd et al., 2013). Lastly, matches are also found to accumulate greater PlayerLoad™ when compared to training sessions (Boyd et al., 2013), supported by findings mentioned in section 2.4 when referring to training load. When activity is of low velocity (<2 $m \cdot s^{-1}$), PlayerLoad™, specifically PlayerLoad™Slow, is inconsistent suggesting, accelerometers may be beneficial tools to utilise when looking at low velocities as other technology such as GNSS devices that contain accelerometers may underestimate PlayerLoad™ resultant from issues with satellite access for such low level activities (Boyd et al., 2013).

PlayerLoad™ as measured through accelerometers also has the capability of providing information that can indicate neuromuscular fatigue in elite soccer players (Rowell et al., 2018). Athlete's activity profiles were seen to change during a standardised SSG as a result from a change in the athletes movement strategy which is correlated to a greater contribution from the mediolateral aspect of their PlayerLoad™ , suggesting standardised SSG are a good tool to use in identifying neuromuscular fatigue (Rowell et al., 2018).

Accelerometers are beneficial to practitioners given they are a cheaper tool when used on their own (i.e., not housed within a GNSS unit) to quantify accelerations. However, accelerometers do have several limitations. The overruling limitation using accelerometers, is they do not account for the position of the player in space therefore velocity, displacement and total distances cannot be quantified (Boyd et al., 2013; Osgnach et al., 2010; Varley et al., 2012a). In AF specifically, practitioners heavily depend on velocity and total distance metrics to aid in training prescription/design and also to make real time adjustments during training sessions if needed (Aughey, 2011). Therefore, wearable sensors that track player positions would be better suited to sports where coaches are interested in velocity and distance.

2.5.1.3 Global Navigational Satellite Systems

Team sport support staff often use GNSS to measure the distance covered by athletes through tracking positional differentiation (Bourdon et al., 2017; Scott et al., 2016). Different GNSS device manufacturers use different sampling frequency ranging from 1 Hz to 15 Hz, where higher sampling frequencies appear to increase the validity and reliability of GPS devices (Jennings et al., 2010a). There is evidence to support 5 Hz surpassing 1 Hz (Jennings et al., 2010a) and for 10 Hz surpassing 5 Hz (Varley et al., 2012b), however, research on 15 Hz in comparison to 10 Hz does not show any significant changes (Johnston et al., 2014) suggesting the effect of sampling rate is only consequential up to 10 Hz (Scott et al., 2016). However, multiple changes in velocity can affect the ability to accurately measure velocity (Varley et al., 2012b), resulting in a level of caution when interpreting any directional metrics i.e., acceleration, deceleration and change of direction (Bourdon et al., 2017).

Due to the nature of reliability testing, testing for within-unit reliability is extremely difficult as it requires human participants to identically replicate exercise with all of the same metrics (Bourdon et al., 2017). The way to account for this or lessen the variance of potential within-unit discrepancy is to fit athletes with the same GPS device on every occasion (Jennings et al., 2010b). Metrics that can be determined using GPS devices include, distance (m) and velocity (Akenhead et al., 2016; Ritchie et al., 2016). Velocity can be further broken down into different speed thresholds i.e., sprints; >7 m/s (Bourdon et al., 2017), high velocity distance; >5.5 m/s $m \cdot s^{-1}$ (Lazarus et al., 2017) , high accelerations; >3 $m \cdot s^{-2}$ (Bourdon et al., 2017; Lazarus et al., 2017) and decelerations; <-3 $m \cdot s^{-2}$ (Lazarus et al., 2017). Acceleration, can also be calculated as the rate of change of speed and can be reported in various thresholds i.e. acceleration efforts (Wisbey et al., 2010) or acceleration load (Thornton et al., 2020; Thornton et al., 2022). There is also the ability to change these velocity thresholds with the platforms provided by the product manufacturer.

2.5.1.4 Local Positioning Systems

Local positioning systems are often used for highly specific purposes to utilise their advantageous properties when compared to GPS units. Advantage of LPS units include; higher sampling frequencies (Gray et al., 2010), ability to function indoors and inside stadiums (Buchheit et al., 2014; Frencken et al., 2010), greater accuracy in determining players positions (Ogris et al., 2012), smaller physical units (Seidl et al., 2016) and supporting tactical analyses (Ogris et al., 2012). Due to the localisation of the antenna in relation to the data collection area, LPS units are able to sample at higher frequencies (Stevens et al., 2014). KINEXON ONE is an LPS unit that samples at 20 Hz (KINEXON Precision Technologies, version 1.0, Munich, Germany). However, 20 Hz LPS units have greater outliers due to greater measurement errors when compared to 10 Hz GPS units (Hoppe et al., 2018). There are also limitations in using LPS units that can affect the data collection including; weather and environmental conditions e.g. heavy fog, snow, hail, tall buildings, industrial area (Siegle et al., 2013), data cleaning techniques e.g. signal loss, missing data points (Stevens et al., 2014), and the position of the antenna relative to the units e.g. middle of the field vs far left corner of the field (Sathyan et al., 2012). Resultant from their limitations, LPS is not a common monitoring tool used within AF.

2.5.2 Quantifying Internal Load

Internal training load is derived from biological measures such as heart rate, blood lactate concentration, oxygen consumption, wellness questionaries, psychological inventories and rating of perceived exertion, taken from athletes during training or competition

(Bourdon et al., 2017). Athletes' psychological readiness or vulnerability can be affected by factors including recovery potential, exercise capacity, non-training stressors and stress tolerance (Bourdon et al., 2017). Considering the vast effects psychological stressors can have on athletes training responses, it is important to incorporate some form of psychological monitoring tool apart of athletes regular training monitoring. The most commonly used inventories include; profile of mood states (POMS), rating of perceived exertion (RPE), session-RPE and the Recovery-Stress Questionnaire Sport (RESTQ-Sport) (Bourdon et al., 2017). Using daily monitoring tools to measure athletes psychological state has the potential to provide an insight into how athletes are responding to training (Kenttä et al., 2006) which can assist coaches in specifying and individualising training prescription (Philippe et al., 2017).

2.5.3 Subjective Load Measures

2.5.3.1 Rating of Perceived Exertion

Rating of perceived exertion is a subjective scale used to measure the level of strain and heaviness experienced during training (Day et al., 2004) and the most commonly used scale is the Category Ratio (CR)-10 created by Borg (1990), however this scale is often adapted for general use within novice through to elite environments which can be seen in figure 2 – 6 (McLaren et al., 2022). Borg's CR-10 scale was designed with set integers in arbitrary units whereby athletes were required to select a numeric value representative of easy, moderate or hard, however, the adaptation of this scale has been intern simplified into a 0 – 10 category scale (McLaren et al., 2022). Often the adapted version of the CR-10 scale include colour, facial expressions or paraphrases for athletes to relate their exertion level to, which can project bias onto their answers (McLaren et al., 2022). As RPE is a subjective rating, it relies heavily on athletes being able to accurately interpret their own level of exertion therefore, needs to be introduced early into athletes training so they become familiar with the scale and how to use it effectively to help reduce this bias (Bourdon et al., 2017).

In AF, 87% of the testing cohort reported the most influential factor in making their decision for an RPE value, was the total distance they had completed in their relevant training session (Bartlett et al., 2017). It can also be challenging for athletes to provide accurate RPE values when their training sessions comprise multiple modality types e.g. skills training, conditioning, strength based training etc (Wallace et al., 2008). There is also a limitation when using adapted CR-10 scales, given if the value 10 for example is associated with the colour red or an angry face, the stigma of this colour or expression may impede athletes reflection of their exertion and instead they may adjust their rating to suit the colour they think will be the most pleasing to the coach or fit in amongst the team/training cohort (McLaren et al., 2022). When using these adapted scales, this also removes the validity of the tool being used. In team sport session-RPE (s-RPE) is more commonly reported monitoring tool mentioned throughout the literature. Session-RPE is a variation of using RPE in which the intensity value determined through the CR-10 scale is multiplied by the total duration of training in minutes giving you internal training load in arbitrary units i.e. s-RPE=intensity (RPE) x session duration (mins) designed by Foster (1998).

Session-RPE is better suited to training sessions that incorporate multiple modalities and is useful in team sports allowing practitioners to identify athletes' responses to training individually to further aid future training prescription (Wallace et al., 2008). Subjective monitoring tools such as s-RPE can further support objective findings, such as the known significant difference in the training load prescribed in pre-season compared to in-season, where there has been a positive statistical significance reported between s-RPE values across the two phases (Moreira et al., 2015).

In AF two different category ratio scales developed by Borg (1982) have been reported, being CR-10 and CR-100, to record s-RPE during skill-based training sessions over 13 weeks (Scott et al., 2013). The key difference between the CR-10 and CR-100 scales is the CR-100 provides more options for athletes to use given the scale comprises a larger number scale. Scott et al. (2013) reported s-RPE is a valid tool to use in quantifying external training load accumulated in AF, where the CR-10 scale had slightly larger correlation coefficient with intensity and training load suggesting there are no limitations when using the CR-10 compared with the CR-100 scale. There was however, notably an issue with reliability with regard to small changes in short exercise intensity efforts, however, reliability was found to increase with higher exercise intensity (Scott et al., 2013). To try and increase reliability within the results, athletes need to be asked the same lead up question every time to try and reduce subjective bias (Menaspà et al., 2017).

Rating of perceived exertion data is reliant on face-to-face interaction between athletes and practitioners to be able to ask athletes the question of how they would rate their level of exertion. However, that is not always possible as they may not always be together pre-training, during training and post-training which has increased the use of new technologies to record equivalent data which can be done electronically and/or self-paced (Menaspà et al., 2017).

0	Rest
1	Very, very easy
2	Easy
3	Moderate
4	Somewhat hard
5	Challenging
6	Hard
7	Very hard
8	Very, very hard
9	Nearly maximal
10	Maximal

Figure 2–6 Example of an adapted Borg Category Ratio (CR) -10 scale (Borg, 1982) used in field setting..

2.5.3.2 Athlete Reported Outcome Measures

Athlete Reported Outcome Measures (AROMs) are tools that can be implemented into standard athlete monitoring practices and are used to provide insight into athletes subjective load (McLaren et al., 2022). These tools are designed for athletes to reflect on their own emotions towards training and/or match/competition stimuli. There are various AROMs utilised and implemented through sports from varying competition levels, whereby it is the discretion of the practitioner within the club/team as what to what tool they deem practical in their setting and whether the tool is validated or an adaptation (McLaren et al., 2022)

With any monitoring tools there are limitations whereby, RPE results can be impeded by logistical limitations and also the nature of training being multifactorial where, internal, as well as external measures can affect training load (Gallo et al., 2015). Rating of perceived exertion, as well as AROMs heavily experience limitations around bias, which can be impacted by both cognitive and situational factors (McLaren et al., 2022). These types of bias include but are not limited to; not understanding the difference between fatigue and exhaustion, comparing exertion to other sessions, the reason behind why they feel their particular exertion level. i.e., training session or other factors, trying to impress others, deliberate deception or reduced intensity and/or volume through participation or lack there of (McLaren et al., 2022). To counteract the bias induced from these tools, practitioners need to ensure athletes have a clear understanding of the tool, how to interpret their exertion and increase their motivation to respond accurately and truthfully (McLaren et al., 2022).

In regard to the greater emergence of AROMs, there is an issue around the lack of validation and clear conceptual framework of the tools being utilised given they are often derived in house from practitioners (Jeffries et al., 2022). The obvious issue with this becomes how can data be meaningful and compared amongst cohorts, teams and also against oneself. Jeffries et al. (2022) designed a conceptual framework that clearly outlines a meaningful way to administer AROMs that provide a validated method to interpret athletes subjective load (figure 2 – 7).

Two common types of AROMs (psychological questionaries and wellness monitoring) implemented in elite sport will be discussed in the proceeding sections.

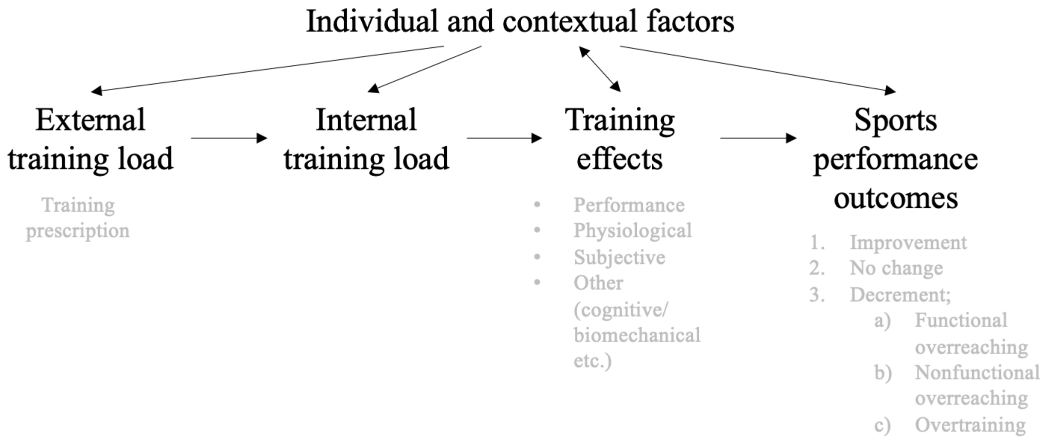

Figure 2–7 Conceptual framework structure designed to assist in designing AROMs adapted from Jeffries et al. (2022).

2.5.3.2.1 Psychological questionnaires

Profile of mood states (POMS) is the longest standing questionnaire that has been used in elite sport (Beedie et al., 2005) and assesses; anger, confusion, depression, fatigue, tension and vigour (Lan et al., 2012). Profile of mood states was developed and validated originally in a clinical setting before being applied to athletes, where it has been applied in multiple individual sports such as distance running, speed skating, Olympic wrestling and team sports such as soccer, basketball and netball (LeUnes & Burger, 1998), where there has been a recent meta-analysis published summating all of the findings (Lochbaum et al., 2021).

Specifically, looking into the application within soccer, the questionnaire was administered pre and post training where the results demonstrated a small to large correlation of pre-post training scores for the different categories assessed using POMS (Selmi et al., 2018). It was identified as a useful strategy to detect the current subjective rating from athletes after an intense training session however, does not have any long term transferability (Selmi et al., 2018). Despite the ability in being able to provide a subjective indication of the athlete, POMS has limitations such that the measure is not sensitive enough to distinguish whether the athlete's subjective feeling is a mood or emotion and it also requires a reasonable amount of time due to the amount of questions, which is often not very practical in an elite environment with multiple training session per week (Lan et al., 2012).

The recovery stress questionnaire-sport (REST-Q Sport) has gained popularity in individual elite sport and is a valid and reliable measure of stress and the frequency of recovery activities which inherently provides information on athlete's state of recovery (Davis et al., 2007; Kenttä et al., 2006). The REST-Q Sport asks questions targeted at the following categories; emotional, psychological, cognitive, behavioural/performance and social stress (Philippe et al., 2017). These questions then provide information in the form of a total stress score and total recovery score which are an indication of physical strain or exertion and potential overload on the athletes (Kellmann, 2010). Within elite soccer, athletes who completed the REST-Q Sport reported no substantial differences within their total stress or total recovery scores (Meister et al., 2013). The lack of statistical support provides no indication about the athlete's strain or exertion, therefore no further insight as their subjective state (Meister et al., 2013). Despite these nil findings, there are also limitations with using such questionnaires as they are not time efficient due to the amount of questions apart of the REST-Q Sport. Subjective measures such as rating of perceived exertion (RPE) or wellness are much more heavily reported in the literature surrounding team sports as they are quicker alternatives which can provide meaningful data (Gastin et al., 2013) and will be explained in the following sections.

2.5.3.2.2 Wellness Monitoring

Wellness monitoring is often completed through questionnaires, incorporating physical, emotional, intellectual, social, environmental and spiritual assessments (Swarbrick, 2006). In elite sport the self-reported questionnaires are commonly created by high-performance practitioners, so they remain specific to their sport and typically involve questions around; muscle soreness, sleep duration and quality and general wellness (Gallo et al., 2015; Gallo et al., 2017). In Australia and New Zealand, of 50 elite sporting programs across 14 different sports surveyed, 84% of high-performance practitioners use self-reported questionaries, where 80% of that use custom designed questionnaires (Taylor et al., 2012). Through making these questionnaires specific to the sport and questions of interest, it allows practitioners to draw meaningful conclusions about the athletes subjective response to training or matches and monitor for any cognitive fatigue (Gallo et al., 2015).

Previous research in AF, specifically within one AFL team, used a customised wellness monitoring tool where data was recorded every day before training for the study duration found that the first day post-match was the best indicator for how the athlete was feeling (Gallo et al., 2017). Interestingly, there was a notable difference in wellness scores recorded when comparing the match to match microcycle length i.e. days in between each match, where 8-day microcycles had a lower wellness score compared 6 and 7 day microcycles (Gallo et al., 2017). There was also a decrease in wellness reported as the season progresses, where weeks 2-12 had a higher wellness score compared to the later stages of the season being weeks 13-23 (Gallo et al., 2017). Another study conducted in AF confirmed match to match microcycle length having significant effects on athletes wellness profiles, where longer microcycles reflect lower wellness profiles (Gastin et al., 2013). This reduction in wellness scores from longer match to match microcycles is also evident within other team sports such as rugby league (McLean et al., 2010). These differences in wellness scores resultant from different microcycle durations suggest there are other factors influencing the athletes internal load as reflected by their wellness (Gallo et al., 2017).

There are known psychological factors that can influence an athlete's training capacity that may not be reflected in common wellness monitoring i.e., team tactics/what team they may be playing in the next match, environmental conditions, relationship with team mates/coaches/staff, whether the next match is a home or away game and the effect of travel if it is an away game (Halson, 2014). Accounting for these factors is extremely difficult as there are multiple situational and cognitive factors that threaten the validity of wellness monitoring (Saw et al., 2015a). Examples of these factors include; comprehension (Brener et al., 2003), recall (Brener et al., 2003) and conscious bias (over-reporting/under-reporting) (Vinokur et al., 1979). Traditional validated questionnaires i.e. RESTQ 36 – sport (Kellmann & Kallus, 2001) typically contain more questions and are designed to collect more meaningful data however, as previously mentioned, are often too time consuming or repetitive to administer in a practical setting (Gastin et al., 2013). Hence why the questionnaires are often designed by the high-performance practitioner as the quality and quantity of questions are designed from empirical measures and personal experience with the nature of the players (Saw et al., 2015a).

2.5.4 Internal and External Load Integration

Although training load is often monitored separately, combining external and internal load provides a greater insight as to whether athletes are fresh or fatigued as you are combining the actual work completed with the impact of the work (Bourdon et al., 2017). There has been vast research conducted in team sports analysing the relationship between internal and external training load, where the correlation effect size varies from trivial to very large (Bartlett et al., 2017; Gallo et al., 2015; Lovell et al., 2013; McLaren et al., 2018; Scanlan et al., 2014; Scott et al., 2013; Weaving et al., 2017; Weaving et al., 2014; Weston et al., 2015). The spectrum of variation must implicitly be resultant from issues with validity and reliability of either internal or external measures (Lambert & Borresen, 2010). However, external measures are heavily tested for their reliability and validity in literature leaving internal load to be questionable, or the nature of the data collection itself (Lambert & Borresen, 2010). The research mentioned draws from various regimes with varied duration, modalities, goals and overall structure which may all heavily influence the relationship found between their specific internal and external load measures (McLaren et al., 2018). Emphasising the need to find and implement the most accurate and applicable testing measures to your sport and training program to target collecting relevant, meaningful data.

The combination of training load is increasingly important in AF due to the complex nature of the sport – unpredictable change of direction/pace and the physical collisions i.e. tackles which all contribute to their overall load (Gallo et al., 2017). Previous research in AF found moderate and large correlations between internal and external load, more specifically between s-RPE and GPS variables where total distance covered (m) and high-speed running (m) showed the strongest correlations ($\rho = .77$ [95% CI = .75–.79] & $\rho = .69$ [95% CI = .67–.71], respectively) (Bartlett et al., 2017). This is supported by research in elite rugby league where total session distance (m), accelerations and “body load” account for 62% of variation between s-RPE (Lovell et al., 2013).

2.6 Monitoring Training

Monitoring is a challenge in team sports due to the nature of the training sessions (Halson, 2014). Training sessions often combine general conditioning, skills conditioning, resistance training and potentially other modes of training i.e. pool sessions, rehab sessions, additional positional drills (Farrow et al., 2008). Despite the physical fatigue athlete's accumulate from training, there is also cognitive fatigue from decision making that is often neglected or harder to monitor (Halson, 2014).

2.6.1 Monitoring through match events

Tracking player contributions in games is often done through statistical analysis (Wright et al., 2013). Player tracking can aid coaches and support staff for means of recruitment or in the immediate term, such as player selection for the next game (McIntosh et al., 2018a). Determining whether a player will be selected or not relies on a spectrum of variables dependent on the variables deemed necessary for that role and how well a player is performing in these areas (Tavana et al., 2013; Trninić et al., 2008).

2.6.1.1 Objective monitoring

In AF, there are five match event types; disposals, possessions, stoppages, defence, and scoring (StatsPro, Australian Football League, Melbourne, Australia) which include the match events listed in Table 2-3. Detailed descriptions of what each match event entails are outlined in Table 2-4. With the ability to assess players value and involvement in a game this is a form of performance tracking which in turn can measure an athletes level of performance periodically when tracked regularly (McIntosh et al., 2018a; Ofoghi et al., 2013). The match events in AF mentioned are collected for every AFL game played therefore a player's performance can be monitored across an entire season using these match events. Champion Data© (Champion Data Pty Ltd., Melbourne, Australia) records player ratings and player rankings for every AFL game played. Player ratings are designed to place value on specific actions completed by players and award points accordingly. Points can either be gained or deducted based on whether players match involvements increase or decrease their teams chance of scoring directly relevant to the involvement the player just had (McIntosh et al., 2018b). Again, there are five different category types identified by Champion Data© for player ratings which include 11 different categories shown in Table 2-5. Player rankings is a model developed to identify the most important performance indicators and includes over 100 variables and is used for fantasy competitions (McIntosh et al., 2018b, 2019). Some match events are predominately or even exclusively completed by some playing roles such as hitouts (McIntosh et al., 2018a), which are almost exclusively completed by ruckman as defined by their role (Johnston et al., 2018). There are other match events which are key defining events such as stoppages, which determine whether a player is a midfield-forward, general forward or key forward (McIntosh et al., 2018a). The issue with using Champion Data© player ratings to define playing roles is that the player classifications change throughout a season as players can change roles between games and also within the game itself, therefore these classifications do not account for players variation between roles (McIntosh et al., 2018a).

Table 2–3 Match events within an AFL game (StatsPro, Australian Football League, Melbourne, Australia).

Match event type	**Match event**
Disposal	Disposals, kicks, handballs, inside 50s, disposal efficiency, clangers, rebound 50s, effective kicks, kick efficiency, kick to handball ratio, effective disposals, metres gained
Possession	Contested possessions, uncontested possessions, intercept possessions, turnovers, contested possession rate, ground ball gets, forward 50 ground ball gets
Stoppage	Hitouts, centre clearances, stoppage clearances, total clearances, hitouts to advantage, hitout win %, Hitouts to advantage %, ruck contests
Defence	Tackles, tackles inside 50, pressure acts, defence half pressure acts, spoils, contested defence one on ones, contested defence losses, contested defence loss %
Scoring	Goals, behinds, goal assists, goal accuracy, shots at goal, score involvements, score launches

% Percentage

Table 2–4 Glossary list of match events in AFL taken from Champion Data© Pty Ltd., Melbourne, Australia.

Match event	Description
Behind	A minor score, as judged by the goal umpire. Behinds are worth one point to a team's total score.
Clanger	An error made by a player resulting in a negative result for his side. Disposal clangers are any kick or handball that directly turns the ball over to the opposition. Frees and 50-metre penalties against, No Pressure Errors, Dropped Marks and Debits are all included in clangers.
Clearance	Credited to the player who has the first effective disposal in a chain that clears the stoppage area, or an ineffective kick or clanger kick that clears the stoppage area.
Contested possession	A possession which has been won when the ball is in dispute. Includes looseball-gets, hardball-gets, contested marks, gathers from a hitout and frees for.
Disposal	Legally getting rid of the ball, via a handball or kick.
Goal	A major score, as judged by the goal umpire. Worth six points to a team's total score.
Goal assists	Creating a goal by getting the ball to a teammate either via a disposal, knock-on, ground kick or hitout, or by winning a free kick before the advantage is paid to the goal scorer.
Ground ball	Sum of looseball-gets and hardball-gets.
Handball	Disposing of the ball by hand.
Hitout	Knocking the ball out of a ruck contest following a stoppage with clear control, regardless of which side wins the following contest at ground level.

Inside 50	Moving the ball from the midfield into the forward zone. Excludes multiple entries within the same chain of possession.
Possession	When a player grabs the ball with a reasonable amount of time to dispose of it. Includes groundball-gets, marks, handball receives, effective contested knock-ons and frees for.
Pressure acts	*Chasing:* Where a player applies pressure from behind an opponent by chasing. They must be gaining ground or applying pressure significant enough to hurry the ball carrier to dispose of the ball. If the chasing player is on the verge of making physical contact from behind, then closing pressure will be imminent. *Closing:* A higher degree of pressure than corralling, where the pressure player is on the verge of making contact with the ball carrier (either from in front or the side) as he disposals of the ball. The key point of difference between this and corralling is that there will be imminent contact and the pressure player is forcing the ball carrier to dispose of it immediately. *Corralling:* The lowest form of pressure a player can apply, where they are simply occupying space in front of the ball carrier to prevent them moving forward, or have a run at them, but not quickly enough to record 'closing' pressure. *Implied:* Reducing an opponent's decision-making time without physical contact 'via corralling, closing space or chasing from behind'. *Physical:* Applying direct physical contact to a player in the act of disposing of the ball or effecting a tackle that prevents an effective disposal from the ball carrier.
Rebound 50	Moving the ball from the defensive zone into the midfield.
Ruck contest	Starting as one of the two ruckmen competing for the ball at a stoppage.
Score involvements	Number of scoring chains where a player was involved with either a disposal, hitout-to-advantage, kick-in or knock-on. If a player has two disposals in the same scoring chain, he is credited with one score involvement.

Score launches	Scoring chains launched by an intercept possession, free kick, hitout-to-advantage or clearance.
Spoils	Knocking the ball away from a marking contest preventing an opponent from taking a mark.
Stoppage	Set pieces where the ball is returned to play after a goal, an out of bounds or a ball up being called. There are three stoppages; Centre Bounces, Ball-Ups and Throw-Ins. Additionally, throw-ins and ball-ups are also referred to as around the ground stoppages.
Tackle	Using physical contact to prevent an opponent in possession of the ball from getting an effective disposal.
Turnover	Losing possession to the opposition in general play. General play excludes events that happen between a stoppage and the clearance.

Table 2–5 Champion Data© categories for AFL player ratings taken from (McIntosh et al., 2018a).

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

2.6.1.2 Subjective performance evaluations

Subjective performance is evaluated publicly in the AFL through awards such as the best and fairest (Charles Brownlow medal) and the AFL Coaches Association award. Votes are submitted at the end of each match during the home and away AFL season, based on a players influence and impact on the game for both awards, the only difference is the best and fairest votes are submitted by the umpires of the game and the latter, the senior coaches of the competing teams. Australian Football League clubs also record subjective ratings tallied for their own best and fairest which can be seen in Table 2-6. Each club has a different approach to tallying the results for their respective best and fairest awards and is further explained in Table 2-6. The methods vary from coaches to committee members being the ones to cast the votes and voting scales ranging from 0-22 with the most common method range being 0-5, used by five teams in the AFL (Sports, 2018). It is common for coaches to provide subjective feedback to the players and be the ones to vote for such awards (Heasman et al., 2008), however over time research has found bias with this. Heasman et al. (2008) listed four reasons to approach coaches subjective ratings with caution; (1) large teams have too many players to be equally invested with all players to be able to accurately assess their performance, (2) personal or emotional bias towards specific players based on relationships developed, (3) match events occurring on the edge of play or not necessarily in the direct line of play may be oversighted and (4) match events towards the end of the game are recalled more vividly compared to the beginning or middle of the game (Franks & Miller, 1986). This issue with biases in subjective methods is also evident with players whose positions automatically give those players more time in focus (Martínez & Martínez, 2011).

Previous research in basketball discusses a bias between players that are named the most valuable player and their perceived ratings as, greater rebounds, assists and points, increases players exposure to the media which in turn generates greater revenue aiding in greater chance of being seen as "valued" (Martínez & Martínez, 2011). In AF, this bias can be seen for players that play as midfielders, as their role requires them to trail the ball through the centre and both forward and defensive halves, they are often involved or associated with more success in the team when compared to a full back (McIntosh et al., 2019). This bias is evident through past winners for the past 10 consecutive Charles Brownlow Medal all being midfielders of midfielder forwards (https://www.afl.com.au/) as these are the players typically with the most play involvement (Johnston et al., 2018). It can be argued that coaches know their players role best and despite the bias existing, subjective ratings are still a feasible tool to use as it provides context to objective measures and this bias, although cannot be ignored, can be accounted for.

Table 2–6 AFL best and fairest awards derived from internal subjective player ratings (Sports, 2018).

AFL Club	Best and Fairest award	Scale for voting points
Adelaide Crows	Malcom Blight Medal	0-4*
Brisbane Lions	Merrett-Murray Medal	Up to 12*+
Carlton Blues	John Nicolls Medal	1-16*
Collingwood Magpies	EW Copeland Trophy	Up to 22*+
Essendon Bombers	Crichton Medal	0-5^
Fremantle Dockers	Doig Medal	0-5*
Geelong Cats	Carji Greeves Medal	Up to 15*+ (averaged between coaches)
Gold Coast Suns	Club Champion	0-5*+
Greater Western Sydney Giants	Kevin Sheedy Medal	Up to 4*
Hawthorn Hawks	Peter Crimmins Medal	Up to 16*+
Melbourne Demons	Keith Truscott Medal	0-10^
North Melbourne Kangaroos	Syd Barker Medal	Up to 20*+

Port Adelaide Power	John Cahill Medal	0-5*
Richmond Tigers	Jack Dyer Medal	0-5^
St Kilda Saints	Trevor Barker Award	1-4*
Sydney Swans	Bob Skilton Award	Up to 10^+
West Coast Eagles	John Worsfold Medal	1-3^
Western Bulldogs	Charles Sutton Medal	Up to 5*+

*Coaches voted ^Committee voted +Non-compulsory vote

2.7 Data Mining

Data mining is a process of gathering information from large databases and using various methods to establish meaningful relationships and patterns that were previously unknown (Ofoghi et al., 2013). The point is to convert raw data into information (Ofoghi et al., 2013) through predicting events (Anagnostopoulos et al., 2007), finding the pattern between events that co-occur (Agrawal et al., 1993) or the division of data into groups according to similarity (Berkhin, 2006). Although some patterns or conclusions may be discoverable without the use of data mining, these inferences can be over or under interpreted due to lack of consideration or understanding certain variables that may impact the data (Ofoghi et al., 2013). By eliminating the human error through using data mining techniques this can produce more reliable and consistent results that have the capacity for comparison (Schumaker et al., 2010). In an applied sport setting according to Ofoghi et al. (2013), data mining typically seeks to answer four aims; (1) Finding performance patterns that describe how an athlete or a team may increase their chances of finishing a competition in a certain position. (2) Predicting performances of an athlete or team given information related to their prior performances or training sessions. (3) Real-time decision-making on what actions/reactions or strategies are required in the course of a current event. And, (4) finding the main demands of certain sport competitions and selecting athletes who can best address the demands. (p. 181)

There are two different divisions of data mining; supervised and unsupervised learning. Supervised learning refers to using methods when you want to predict the value of an observation, a single output variable i.e. linear regression, time series, regression trees, k-nearest neighbor (Talabis et al., 2015). Unsupervised learning comprises methods trying to understand and describe data to reveal underlying patterns i.e. clustering, association analysis, principal component analysis (Grira et al., 2005). The different learning approaches can be used independently, however they are often used in conjunction to strengthen the meaning behind the patterns found in unsupervised approaches (Saha et al., 2011). Choosing the right approach depends on the interpretability, precision and flexibility of the chosen method (Ofoghi et al., 2013). Figure 2-8 demonstrates the relationship between choosing the most appropriate data mining technique and the considerations taken to arriving at this decision.

Sports Performance Analysis Requirements	**Major Data Mining Methods**	**Data Mining Techniques**	**Data Mining Technique Characteristics**
Performance pattern discovery	Clustering	*K*- means	Interpretability
Performance prediction	Classification	Decision trees	Precision
Real-time decision-making	Relationship modelling	Bayesian networks	Flexibility
Demand analysis	Rule mining	Support vector machines	
		Regression analysis	

Figure 2–8 Rectangular Model illustrating the considerations between choosing the most relevant data mining technique for sports performance analysis adapted from Ofoghi et al. (2013).

2.7.1 Visually representing data

Data is something that can be presented in multiple ways whereby the choice is often based on the aim for why the data is collected. Being able to visually represent data is an important skill as it can be much easier and clearer to convey your point visually (Wilke, 2019). Despite this, data visualisation is a topic not often taught, and when taught it focuses on the visual effects and the techniques behind making the figures look how they do, rather than the education behind why some decisions are preferential over others in choosing what to visually represent (Wilke, 2019). There are multiple aspects to be considered when visually representing data which can easily be overlooked or not considered with much thought such as the graph type, colour used (or not used), position of the axes and data, lines/shapes used to identify data points and the width/size of data markers (Wilke, 2019). Regardless of these factors, there are two groups in which data is categorised by, continuous, where there are arbitrarily multiple instances possible between two given numbers i.e. data set using total distance, you can physical have 1000 m, 1000.1 m 1000.2 m etc., or non-continuous, where there are no instances possible between two given numbers as it is a physical impossibility i.e. number of athletes recorded where you can have 5 or 6 but not 5.5 (Wilke, 2019).

2.7.1.2 Data visualisation options

There are multiple options to choose from when visualising data, which makes the task challenging as you need to select the method which is going to display the best relationship for the question you have or the purpose behind the data collection. Wilke (2019) reported four main methods for visually data and their respective benefits and limitations which will be discussed and applied below.

- **Histograms**
  The use of histograms can distribute data into ranges which can be manipulated as seen fit to display a distribution of how data is spread across the scale in question. The issue with this method, is the human error involved in choosing the ranges in which data is spread between as ranges too low can reduce the true context within the data and too many ranges can represent closer to singular data points therefore, not summarising the data set which can be seen in Figure 2-9. It takes multiple trial and error to find the number of ranges most applicable to the data set. Secondly to this, when investigating multiple distributions using a histogram, the data may be harder to interpret given the second data set/comparison either won't align with the zero mark from the *y* axis therefore, you need to visually determine the effect, or

alternatively both data sets can be made translucent and positioned at the zero mark on the *y* axis, however, when made transparent this can cause further visual errors. For a singular distribution analysis this type of visualisation may be useful, or for when ranges are discrete metrics rather than continuous i.e., pre-season phases along the *x* axis and total distance accumulated along the *y* axis. This would alleviate the need to determine the number of ranges required and is a singular distribution.

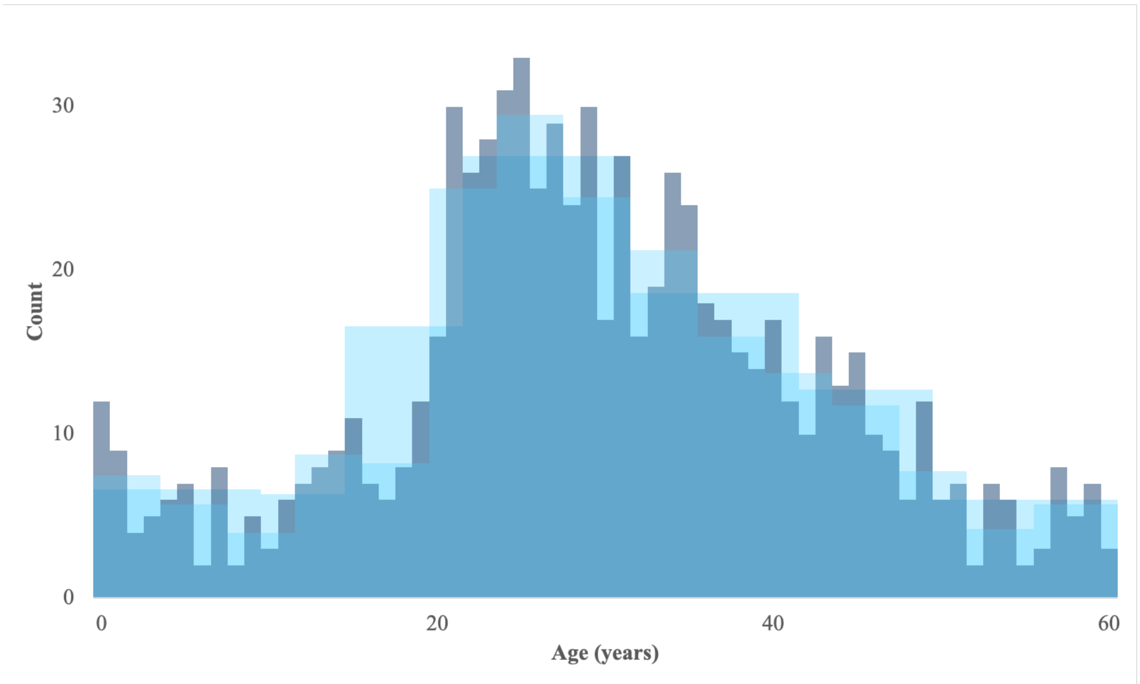

Figure 2–9 Histograms displaying the effect of the distribution when using different ranges i.e. different amount of years in each range demonstrated by different colours for the above example adapted from Wilke (2019).

- **Density plots**

  Density plots can visually display the probability of a distribution and can then have a curve fitted to the data points to visual display the distribution where the total area under the curve is equal to one. However, the issue with fitting the curve, is again the effect of human error, where different techniques can be applied which can result in different visualisations which can be seen in Figure 2-10. Different techniques can also produce visualisations where the curve reaches particular values that the actual data may not have, based on the calculations to fit the curve. In saying this, density plots are more useful when trying to visual display more than one distribution. This can be applicable when trying to understand the relative contribution of a metric and its coherent effect on another metric whereby the overall number is not of upmost importance and rather the distribution is.

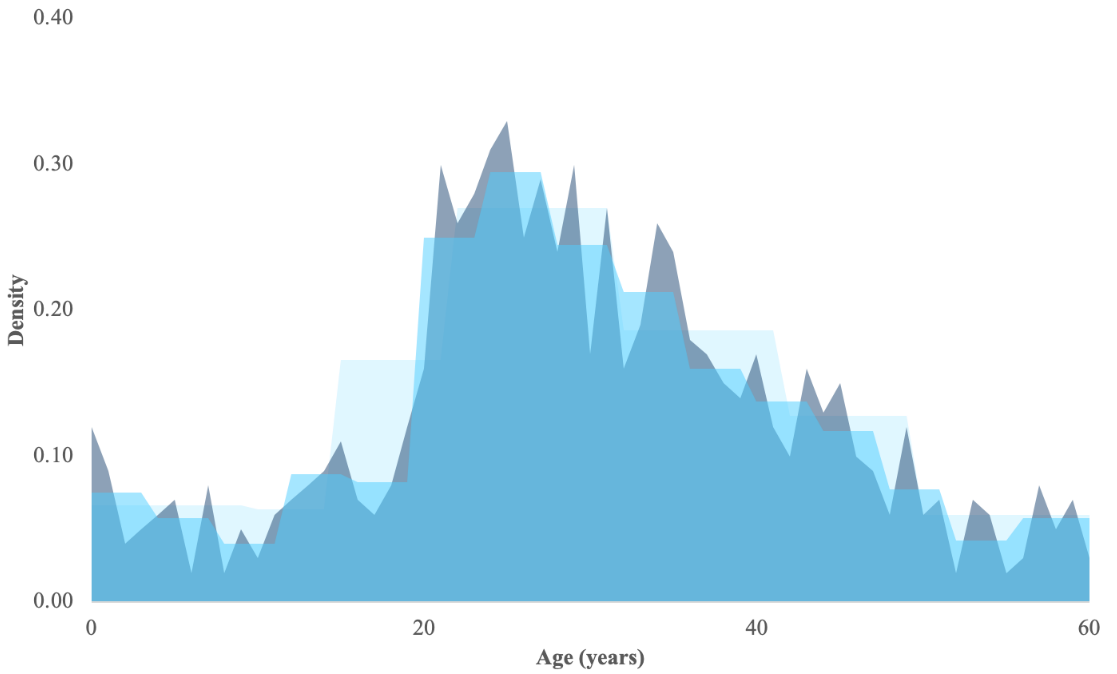

Figure 2–10 Density plots demonstrating the effect of different processing and filtering techniques to the overall visual representation of the data set represented by different colours adapted from Wilke (2019).

- **Empirical cumulative distribution functions**

  Alternatively called cumulative distributions, this method utilises full data sets where no human decision making is required to produce the final figure. There are both ascending and descending cumulative distributions possible, where ascending are the most commonly reported. This type of visual representation plots each individual data point and then a line is inserted connecting the points for the highest value of that variable achieved at that given point (ascending) or the lowest value achieved for that variable at that data point (descending). This method can be useful when handling large data sets in which you want to understand the distribution better, whereby you have the individual data points but want to see how they accumulate, between athletes of over a specific condition i.e. match.

- **Quantile-quantile plots**

  This method is useful for finding the outliers within the data, for when the data points do not follow the expected or given distribution. Actual values achieved are plotted against the expected values obtained according to the distribution identified using this method and a line is then drawn where *x* equals *y*, being where the actual values equal the predicted ones. Then any data points that do not fall on this line are considered to be the outliers as they did not follow the expected distribution. This method could be applicable to an investigation where the response is expected for a given metric, and can be applied to the full team to see if all athletes follow the expected distribution or if there are any that appear to be outliers.

2.8 Australian Football Performance

2.8.1 What is Performance?

Due to the complex nature of individual responses to the vast number of training variables and their effects on training load, training performance cannot equal match performance (Borresen & Lambert, 2009; Foster et al., 1996). Training however, can improve performance in a game by training the physiological, psychological and tactical aspects required in games and can better prepare you (Borresen & Lambert, 2009).

2.8.2 How is Performance quantified/obtained?

Performance can be quantified using various equations and modalities (Borresen & Lambert, 2009). Firstly, there was an equation developed by Calvert et al. (1976) which states performance is the result of fitness, minus fatigue therefore emphasising the need for fatigue to be minimised in order to maximise performance. Banisters model produces estimations that can be used to predict future performance (Banister et al., 1991). Busso et al. (1991) developed a simplified equation using only the fitness impulse which alike Banisters (Banister et al., 1991), produce estimations for performance prediction however, fatigue may be underestimated creating false estimations. Other research has tried to build upon Banisters model (Busso et al., 1991) and validate specific physiological parameters as markers of performance (Wood et al., 2005). For the fitness parameter they found running speed at ventilatory threshold and running economy to be valid markers, however, they found a fatigue subsection of the Profile of Mood States questionnaire could be used for fatigue measure but is not a valid measure as it is not targeted at exercise-induced fatigue (Wood et al., 2005).

Multiple other physiological and psychological parameters have been estimated including Daily Analysis of Life Demands for Athletes test, heart rate variability, resting heart rate, VO_2 max, exercise economy, lactate thresholds and critical power (Jones & Carter, 2000; Lambert & Borresen, 2016). The validity of these parameters has never been conclusive or would encourage the independent use of one sole parameter as there are numerous environmental, mental and tactical factors that can influence performance hence, cannot be predicted (Jones & Carter, 2000). Different to the previous methods mentioned, Fitz-Clarke et al. (1991) developed the theory of using an influence curve to predict future performance based off training impulses. This method cumulates the daily training impulses and based off its initial magnitude will contribute to overall performance, therefore, incorporates the positive and negative influences of each training session (Fitz-Clarke et al., 1991). Resultant from the data the model encompasses, it has the potential to design the optimal training program to produce a given performance at a specific time (Borresen & Lambert, 2009; Fitz-Clarke et al., 1991). The limitation with using this method is that competition will have an effect on subsequent performance, meaning results from a competition will change the optimal training and recovery for that given athlete going forward thereby deviating from the influence curve previously developed (Borresen & Lambert, 2009; Fitz-Clarke et al., 1991).

Another model has been developed by Hellard et al. (2005) using saturation thresholds to monitor athletes training loads. To do so, athletes are exposed to training intensity and durations below their supposed threshold for certain training stimuli to maximise the physiological adaptations and this level (Hellard et al., 2005). This model proved to be more effective in reflecting performance based from training when compared to Banister et al. (1991), however, only accounted for 30% of performance variation (Hellard et al., 2005). This low accuracy was thought to be resultant from athletes' individual responses to training and how responses can change day to day and between different modalities reiterating how athletes all respond unique to the individual (Mann et al., 2014; Vollaard et al., 2009).

All of these methods mentioned have struggled to be used as accurate and reliable measures of performance in elite sport due to their inconsistency or underrepresentation of fitness and fatigue impulses, weak correlations between training and performance and overall lack of individualism opening the door for new methods to be developed or adjustments made to existing models (Borresen & Lambert, 2009).

2.9 Conclusion

Australian Rules football is a very demanding game emphasising the need to monitor players responses to training and determine whether the current training has a positive effect on performance. Players' responses can be monitored through various aforementioned internal and external training modes such as GPS, heart rate and wellness monitoring. It is important that data is analysed in a meaningful way to give context and broaden knowledge to justify its collection. Often analysis involves data mining to develop patterns and relationships that might have been unknown or hidden. As these players train together as a group completing approximately the same external training load, it is extremely important to understand their internal training load to said training. The differences in internal training load between players will help paint the picture as to the inter-individual differences within a team which in turn can aid in more individualised training prescription. If training simulates the physical and movement demands for a match, specific to each individual, this will create the environment for the greatest improvements in match performance. Where increased performance has a direct influence on team success, making it an important area to monitor in any sport at any level.

As there is presently known differences around performance and the difficulties there is in predicting performance, this thesis is driven to investigate firstly, whether the monitoring tools currently utilised by the club practitioners have any transferable correlation with performance, justifying their implementation in the standard monitoring process. Secondly, to introduce a novel technique in which training and match volume is quantified to gain a new perspective. Overall both aims are trying to quantify what is occurring, rather than understand causality and prediction which has been proven so difficult in sport, especially team sports at the elite level.

CHAPTER 3. GENERAL METHODOLOGIES

The specific methodologies applied throughout the thesis will be further explained in their respective chapters, however, for the novel approach of cumulative distribution employed in studies two through four, this will be introduced in this chapter.

3.1 Defining cumulative distribution

Large data sets often expose practitioners to limitations around thresholds or zones in which data is sorted into the be analysed which require an informed decision to be made (Impellizzeri & Bizzini, 2012; Wilke, 2019). Cumulative distribution is a form of aggregate methods whereby large datasets can be visually displayed to account for all data points imported and reduce the limitations associated with data filtering (Wilke, 2019). The ability to provide visualisation alongside statistics can assist practitioners by providing greater context and can also assist in the means of presenting data to athletes, coaches or other practitioners.

3.2 Methodological procedures

3.2.1 Study Design

For all studies, data was collected using GNSS devices (Catapult S7, Catapult Sports, Victoria, Australia) that record at 10 Hz and were Local Positioning System (LPS) enabled. Within each study for the relative comparison made the files were comprised of either GNSS, LPS or a combination of both, where the specific observations are reported in the respective chapters. For all studies, LPS match files have been excluded from the analysis resultant from the invariances between GNSS and LPS data collection (Hoppe et al., 2018). Match and training files were downloaded and trimmed to include only playing/training time via the manufacturer's software (OpenField, version 3.3.1, Catapult Sports, Victoria, Australia). Following the download and trimming process, the match/training files were downloaded from the OpenField console in their raw 10 Hz form as comma-separated files (csv.). The raw files comprised metrics such time (s), speed ($km \cdot hr^{-1}$), acceleration ($m \cdot s^{-2}$), latitude and longitude.

To prepare the raw files for analysis, speed was processed with a fourth-order, 1 Hz low-pass Butterworth filter. For standardisation, acceleration was manually calculated using the 3 point central difference method (Delves et al., 2022) and was not filtered again, it was also made absolute to remove all negative values (Delaney et al., 2018a; Delaney et al., 2018b). A 1-minute moving average was then applied to the speed and acceleration data. Speed was converted to $m \cdot min^{-1}$ and acceleration converted to $m \cdot min^{-1} \cdot s^{-1}$ by multiplying each value by 60 respectively. The volume of speed [distance (m) covered] and acceleration [impulse (N·s) accumulated] was then established with the distribution of these variables categorised into 10 $m.min^{-1}$ and 5 $m \cdot min^{-1} \cdot s^{-1}$ zones for speed and acceleration respectively. The total volume of distance and impulse in each zone across each condition specific to the aim of the study which will be outlined in their respective chapter was calculated.

Visual inspection of the logarithm of the cumulative volume and intensity for both distance and impulse showed a quadratic (non-linear curvilinear) relationship for the varying comparisons. To describe the distribution of distance and impulse across the intensity spectrum quadratic models were established for each player for each comparison specific in each study. For clarity, the "distance speed model" was established as the speed (x) in 10 $m \cdot min^{-1}$ zone versus the logarithm of accumulated distance (y). The "impulse acceleration model" was established as the acceleration (x) in 10 $m \cdot min^{-1} \cdot s^{-1}$ zone versus the logarithm of accumulated impulse.

The quadratic models returned the quadratic coefficient (*a*), linear coefficient (*b*), and intercept (*c*). Where *a* represents the overall position of the curve up and down the y axis (i.e., wide or narrow), *b* reflects the upward or downward linear trend in y values along the x axis, and *c* is a constant (intercept), representing where the relationship sits on the y axis (Duthie et al., 2021).

3.2.2 Statistical Analysis

Linear mixed models were used to compare the quadratic coefficients from each model between comparisons specific to each study. Specifically, in these models, the coefficient (*a*, *b* or *c*) for either the Distance Speed Model or Impulse Acceleration Model was entered as the outcome measure, and the specific comparison of the study was entered as the predictor (fixed effect). Athlete identification was included as a random effect, to account for the repeated measurements within the dataset. The least squares mean test was used to obtain pairwise comparisons of the entered fixed effect, and the resulting SDs and mean differences were used to establish standardised effect sizes (ES) and 90% confidence limits (CL). Standardised ESs were described using the magnitudes; 0.20 trivial; 0.21–0.60 small; 0.61–1.20, moderate; 1.21–2.0 large and 2.01 very large (Hopkins et al., 2009). Differences were deemed to be real if they were 75% greater than the smallest worthwhile difference (calculated as 0.2 x the between-athlete SD).

CHAPTER 4. STUDY 1 – RELATIONSHIPS BETWEEN TRAINING MONITORING AND PLAYER MATCH PERFORMANCE IN PROFESSIONAL AUSTRALIAN FOOTBALL

4.1 Introduction

Training monitoring is the routine management of collating and analysing data collected from players that is a form of training load, either external or internal (Bourdon et al., 2017). External training load is the physical work completed, for example, the distance covered quantified by global navigation satellite systems (GNNS) whereas internal training load is the subjective response to said work e.g. perceived exertion (RPE; (Halson, 2014). The purpose of training monitoring is to track players responses and exposure and provide context to how training load is accumulating (Ritchie et al., 2016). Training needs to expose players to environments as close to those they may experience in a game through manipulation of skills, intensity and conditioning in order to better prepare them to cope with the expected stressors (Rushall, 1990). Through monitoring training responses this provides insight as to whether these demands are being met and if not, which areas are lacking.

The ultimate aim of coaches and staff is to win matches and maximise individual performance (Borresen & Lambert, 2009). Within the AFL staff are able to independently select, process and evaluate data for the metrics and methods they identify best fit to best prepare the players for matches. The metrics collected can range anywhere from physiological to psychological where it is recommended that a combination of both external and internal load is measured (Bourdon et al., 2017). Despite this, GNNS is the only guaranteed technology to be presently utilised at every club, as the AFL is under contract to use this platform. The exact data each club collects is not public knowledge however, common training load measures include wellness diaries (Gallo et al., 2015; Gallo et al., 2016; Gallo et al., 2017), rating of perceived exertion (RPE) scores (Gallo et al., 2015; Scott et al., 2013) and gym-based training (Bilsborough et al., 2015; Johnston et al., 2018) based off published research within the field . Within each of these metrics there are various ways to process and analyse the data which as above, relate to the specific club's discretion and again is not public knowledge unless published.

Player performance is not an easily measured or defined metric. It can be very subjective and indiscrete with multiple ways to record/determine. Champion Data© have created their platform to record real time statistics for every AFL game which then generate ranking and rating points which are used to place value on specific actions completed by players and award points accordingly (Champion Data Pty Ltd., Melbourne, Australia). These statistics are used as a way to quantify an athlete's performance and reduces bias, as the criteria for the ranking and rating points are pre-determined and are the same for each athlete. McIntosh et al. (2018b) conducted a validation study on the Champion Data © rating points, where they were confirmed to be a valid tool for assessing player performance. Where previous other research has been conducted comparing these rating points to subjective performance evaluations (McIntosh et al., 2019) and using the ratings points as a performance marker (McIntosh et al., 2018a). Alternatively to the Champion Data © rating points, coaching staff from each AFL club record their own subjective ratings of performance post-matches, depending on the club there is a different Likert scale used (Sports, 2018). There is a downside to both measures when using them to rate an athlete's performance. Champion Data© is capable of measuring statistics but it does not account for players whose positions do not necessarily accumulate statistics when completing their desired role. For example, a defender's role is to defend the ground from the opposing team scoring a point or goal. In this process a defender does not necessarily need to take marks, kick goals, accumulate possessions, they may simply need to apply pressure and defend their area making their opponent unavailable to receive a possession. If a defender completes their role, they in turn may not accumulate many statistics therefore, when looking at the Champion data© ratings they may rate low. The under representation through Champion Data© ratings may emphasise where coaches ratings can benefit, as the coach knows exactly what they expect of their player so for the same example they may rate this particular defender highly for said game.

It is known monitoring training is important in elite sport to provide insight into how players are responding to training however, it is unclear whether performance can be predicted by said training responses obtained during training sessions. There is no clear gold standard monitoring tool that is guaranteed to predict success in the form of player performance. The manipulation of training and the tools selected to monitor training are based on educational judgments from practitioners within the club or environment, dependent on a multitude of factors. Therefore, this study aimed to determine the club derived individualised characteristic/s that are the most robust in understanding match performance from one AFL clubs standard monitoring process during the 2019 AFL season. Second, the study aimed to determine the relationship between coaches subjective ratings and Champion Data © player ratings. The potential of these results could provide insight as to which methods provide information and which have no direct relationship on performance posing the question as to the justification for why these measures are used.

4.2 Methods

4.2.1 Participants

Forty professional AFL league players (age; 25 ± 4 yr, mass; 87 ± 9 kg and height; 188 ± 7 cm) from a single club volunteered for this study. Data were collected during 24 matches throughout the 2019 competitive season (15 wins,7 losses). The typical training week for players consisted of 2-3 field sessions, 2-3 resistance sessions and 1-2 additional on-legs sessions consisting of either reduced volume, rehabilitation, additional conditioning and skills training depending on the requirements of a player. Players were classified by playing position as follows: forwards (n = 11), midfielders (n = 13) and backs (n = 16). The mean (± SD) number of match observations per player was 17 ± 13. Ethical approval for this research project was granted by the relevant Human Research Ethics Committee (HRE17-138).

4.2.2 Study Design

Data collected consisted of GNSS, local positioning system (LPS), wellness, coaches performance rating and Champion Data ratings©. Both GNSS and LPS were collected through catapult S5 units sampling at 10-Hz (MinimaxX, Catapult Innovations, Australia) for every training session and game. The metrics recorded were total volume, high speed running distance (15-19.99 km·hr^{-1}), sprint distance (>25 km·hr^{-1}), total high intensity running distance (20+ km·hr^{-1}), max velocity and work rate (m·min^{-1}). The wellness questionarrie implemented was an invalidated, adapted AROM designed by the high performance manager of the club and contained 12 questions answered using a 0-10 Likert scale. The questions were split into three categories; readiness to train, soft tissue status and overuse/stress. The questions covered areas such as sleep quality, soreness, mental state and energy levels. Categories were chosen based on specific areas of interest to performance staff as previously described. Coaches' performance ratings were a subjective rating on a 0-10 Likert scale. Every player was rated at the end of every match by the player's relevant line coach. The ratings were based on how well each player performed technically and tactically in their role. A rating of seven or above was judged an acceptable performance and a rating below seven was an unacceptable performance. Each player's line coach allocated the rating. The head coach was allowed to overrule the rating of the line coach, if they deemed it necessary. Champion Data© (Champion Data Pty Ltd., Melbourne, Australia) records player ratings and player rankings for every player in an AFL game. Player ratings are designed to place value on specific actions completed by players and award points accordingly. Points can either be gained or deducted based on whether players match involvements increase or decrease their teams chance of scoring directly relevant to the involvement of the player (McIntosh et al., 2018b).

4.2.3 Statistical Analysis

The player performance metrics were analysed using linear mixed models (Bates et al., 2015). The residual errors of the model predictions were not normally distributed, so the models were generalized to employ non-normal assumptions about the data and the error distributions. The fixed effects in the models included; stage of the season, travel, match outcome, position, playing experience, weather and ground size. The random effects in the model were player identity and match identity. The player performance metrics were then visualised using the *ggplot2* library within the R programming language (Wickham, 2016). The data visualisation informed the specification of the random effects structure of the model, where for each performance metric a separate model was built. The predictor variables were centered and scaled by two standard deviations in order to help with model convergence.

For coaches subjective ratings and Champion Data© player ratings, a Spearman's rank order correlation was applied to determine the strength and direction of the relationship between the two variables.

4.3 Results

Table 4-1 presents the model table for the Champion Data© rating points and coaches subjective ratings compared to wellness. With regard to reporting the results, a combination of traditional hypothesise testing (*p* values) was used in conjunction with effect sizes to assess the magnitude of difference. The mixed models created and their model estimates reflected that there were only two relationships, this first being a negative relationship between soreness and champion ratings (ES = -0.68; 90% CL = -1.30 - -0.06) and secondly a negative relationship between energy and coaches ratings (ES = -0.48; -0.29 - -0.01). The remainder of the models all produced a negative relationship, apart from foot and calf which both had a positive relationship with Champion Data© rating points and coaches subjective ratings, however, none of these relationships were significant to infer statistically meaning from. Table 4-2 presents the model table for the Champion Data© rating points and coaches subjective ratings compared to training GNSS data. The results demonstrate there was no relationship found between Champon Data© rating points and total volume, surge distance and THIR distance from training and also between coaches subjective ratings and totla distance, surge distance, sprint distance, THIR distance and work rate in training reflected through to beta coefficients. Sprint distance and maximum velocity from training demonstrated a negative relationship with Champion Data© rating points as well as maxmium velocity from training and coaches subjective ratings, however, these relationships were not statistically significant. Table 4-3 presents the model table for the Champion Data© ratings points and coaches ratings compared to match GNSS data. The results presented in this table shows the nill relationship between both Champion Data© rating points and coaches subjective ratings when modelled with total volume, surge distance, sprint distance and THIR in macthes. Maximum velocity and work rate both demonstrate a negative relationship with Champion Data© rating points and coaches subjective ratings, however, these relationships are not of statistical significance. Figure 4 – 1 displays the relationship between Champion Data© rating points and coaches subjective ratings, where the vast dsitribution can be seen as there is no significant relationship between these ratings methods.

Table 4–1 Model table for Wellness displaying the estimate (beta coefficient), standard error of the estimate (SE) and confidence limits (CL).

Outcome	Term	Estimate	SE	CL
Champion Data © Player Ratings	*Intercept*	12.20	2.08	8.12-16.29
	Sleep rating	-0.44	0.28	-0.99-0.10
	Intercept	8.51	2.47	3.68-13.49
	Foot rating	0.07	0.34	-0.59-0.72
	Intercept	12.75	2.68	7.51-18.00
	Leg rating	-0.52	0.36	-1.23-0.19
	Intercept	10.60	2.38	5.95-15.27
	Back rating	-0.23	0.33	-0.87-0.41
	Intercept	13.68	2.25	9.27-18.08
	Soreness	-0.68	0.32	-1.30 - -0.06*
	Intercept	10.11	2.52	5.17-15.06
	Quad rating	-0.15	0.34	-0.81-0.51
	Intercept	13.16	2.53	8.21-18.12
	ROM	-0.58	0.34	-1.25-0.09
	Intercept	12.45	2.60	7.34-17.53
	Energy	-0.48	0.35	-1.17-0.21
	Intercept	13.60	3.22	7.29-19.91
	STS/60	-0.11	0.07	-0.25-0.04
	Intercept	12.20	2.51	7.28-17.14
	Groin	-0.44	0.34	-1.10-0.22
	Intercept	12.89	2.53	7.95-17.86
	Hamstring	-0.54	0.34	-1.21-0.13
	Intercept	12.09	2.75	6.66-17.48
	Mental	-0.42	0.36	-1.13-0.30
	Intercept	8.87	2.16	4.64-13.13
	Calf	0.02	0.30	-0.56-0.59
Coaches Rating	*Intercept*	12.20	2.08	6.56-8.18
	Sleep rating	-0.44	0.28	-0.19-0.02
	Intercept	8.51	2.47	5.79-7.69
	Foot rating	0.07	0.34	-0.13-0.13
	Intercept	12.75	2.68	6.21-8.30
	Leg rating	-0.52	0.36	-0.21-0.07
	Intercept	10.60	2.38	6.00-7.85
	Back rating	-0.23	0.33	-0.15-0.10
	Intercept	10.60	2.38	6.73-8.52
	Soreness	-0.23	0.33	-0.25-0.002
	Intercept	10.11	2.52	5.87-7.81

	Quad rating	-0.15	0.34	-0.14-0.12
	Intercept	13.16	2.53	6.50-8.48
	ROM	-0.58	0.34	-0.24-0.03
	Intercept	12.45	2.60	6.79-8.85
	Energy	-0.48	0.35	-0.29 - -0.01*
	Intercept	13.60	3.22	6.12-8.59
	STS/60	-0.11	0.74	-0.04-0.01
	Intercept	12.20	2.51	6.20-8.15
	Groin	-0.44	0.34	-0.19-0.07
	Intercept	12.89	2.53	5.85-7.81
	Hamstring	-0.54	0.34	-0.14-0.12
	Intercept	12.09	2.75	5.89-8.04
	Mental	-0.42	0.36	-0.17-0.12
	Intercept	8.87	2.16	6.03-7.71
	Calf	0.02	0.30	-0.13-0.10

*It can be interpreted that the effect is positive or negative dependent on the direction of the confidence intervals as the interval does not cross zero

Table 4–2 Model table for Training GPS displaying the estimate (beta coefficient), standard error of the estimate (SE) and confidence limits (CL).

Outcome	**Term**	**Estimate**	**SE**	**CI**
Champion Data © Player Ratings	*Intercept*	7.00	1.34	4.32e-9.64
	Total volume	0.00	0.00	-4.81e-0.00
	Intercept	8.29	0.91	6.47-10.08
	Surge distance	0.00	0.00	-0.00-0.00
	Intercept	9.77	0.69	8.38-11.11
	Sprint distance	-0.01	0.00	-0.01-0.00
	Intercept	9.90	0.83	8.25-11.53
	THIR distance	0.00	0.00	-0.00-0.00
	Intercept	10.18	3.08	3.93-16.38
	Max velocity	-0.03	0.10	-0.23-0.17
	Intercept	7.49	2.07	3.22-11.66
	Work rate	0.02	0.02	-0.03-0.06
Coaches Rating	*Intercept*	6.63	0.34	5.963-7.29
	Total volume	0.00	0.00	-8.68e-0.00
	Intercept	6.73	0.22	6.30-7.16
	Surge distance	0.00	0.00	-0.00-0.00
	Intercept	6.91	0.17	6.57-7.25
	Sprint distance	0.00	0.00	-0.00-0.00

	Intercept	6.81	0.19	6.42-7.19
	THIR distance	0.00	0.00	-0.00-0.00
	Intercept	6.60	0.60	5.43-7.87
	Max velocity	0.01	0.02	-0.03-0.04
	Intercept	6.74	0.45	5.86-7.63
	Work rate	0.00	0.00	-0.01-0.01

Table 4–3 Model table for Match GPS displaying the estimate (beta coefficient), standard error of the estimate (SE) and confidence limits (CL).

Outcome	Term	Estimate	SE	CI
Champion Data © Player Ratings	*Intercept*	1.65	1.74	-1.75-5.06
	Total volume	0.00	0.00	0.00-0.00
	Intercept	5.55	1.32	3.96-8.15
	Surge distance	0.00	0.00	0.00-0.00
	Intercept	9.27	0.74	7.76-10.73
	Sprint distance	0.00	0.00	-0.01-0.00
	Intercept	8.35	1.05	6.22-10.45
	THIR distance	0.00	0.00	-0.00-0.00
	Intercept	11.15	3.97	3.36-19.02
	Max velocity	-0.07	0.13	-0.33-0.19
	Intercept	13.92	5.08	3.98-23.86
	Work rate	-0.04	0.04	-0.11-0.04
Coaches Rating	*Intercept*	4.54	0.44	3.68-5.40
	Total volume	0.00	0.00	0.00-0.00
	Intercept	6.18	0.27	5.66e-6.71
	Surge distance	0.00	0.00	5.12-0E-0.00
	Intercept	6.72	0.17	6.39-7.05
	Sprint distance	0.00	0.00	-0.00-0.00
	Intercept	6.41	0.21	5.98-6.83
	THIR distance	0.00	0.00	0.00-0.00
	Intercept	6.91	0.71	5.51-8.29
	Max velocity	-0.01	0.23	-0.05-0.04
	Intercept	7.64	0.91	5.85-9.44
	Work rate	-0.01	0.01	-0.02-0.01

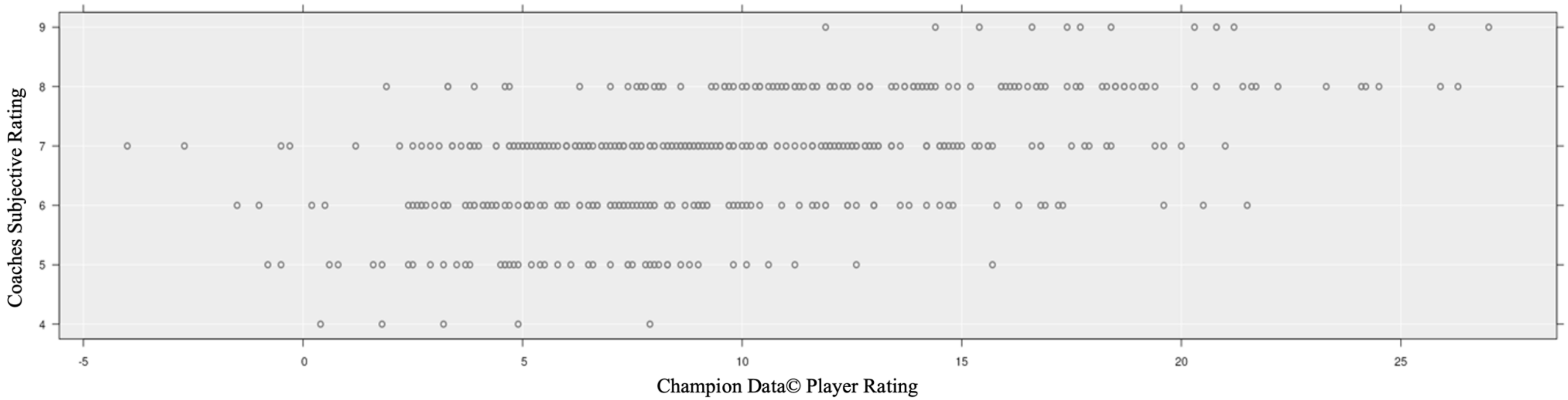

Figure 4–1 Scatter plot showing Coaches Subjective Ratings (AU) vs Champion Data© Player Ratings (AU). Each point represents a single player's match during the AFL season.

4.4 Discussion

The purpose of this study was to investigate the characteristic/s that are the most robust in understanding match performance in AF. A second aim was to identify the relationship, if any, between coaches subjective ratings and Champion Data© player ratings. No meaningful relationships were found from any comparisons throughout this analysis that could be used as a means to predict match performance from any of the monitoring tools analysed. This brings to question whether the measures analysed in this study may be directly useful for the purpose of assessing match performance. Wellness diaries are a known commonly employed monitoring tool (Gallo et al., 2015; Gallo et al., 2016; Gallo et al., 2017), however, from this study only two meaningful relationships were identified, the first being between Champion Data© ratings points and soreness. The direction of the relationship infers players who score higher for soreness will produce lower Champion Data© rating points. Another statistically significant relationship found when analysing wellness, was between coaches subjective ratings and energy whereby the direction of the relationship inferred players with a lower energy rating reported lower coaches subjective ratings in the proceeding match. The lack of relationship between performance and wellness identified in this study, highlights the ineffectiveness of using an invalidated AROM (Jeffries et al., 2022). It can be argued that the use of an invalidated AROM is implemented as a means to drive conversation between players and coaches or performance staff rather than providing a quantifiable performance metric (Saw et al., 2015b).

The relationship identified between wellness soreness scores and Champion Data© rating points suggests as soreness increases, the opposite occurs for rating points. There is a large focus around recovery in elite sport with the aim to reduce soreness where training prescription is finely tuned to provide exposure to training stimuli to maintain performance whilst reducing athlete exposure to injury (Colby et al., 2014; Drew & Finch, 2016; Mujika et al., 1995). Often, recovery sessions or days off are implemented between main training sessions and post matches to provide the opportunity for the players to best prepare for their subsequent competition (Bahnert et al., 2013; Barnett, 2006), where in AF it is known that players require four days post-match to physiologically recover (Cormack et al., 2008). Training is strategically manipulated into different phases during both the pre-season and in season to elicit different goals or maintain capacities depending on the stage of the season (Bompa & Haff, 2009). There is a known reduction in training load during the in season phase which is designed to provide greater opportunity for players to recover between matches (Slattery et al., 2012). However, alongside structured recovery protocols, physical strength and power of rugby league players has been reported in reducing post-match fatigue (Johnston et al., 2015a) which correlates with training prescription. Muscular strength and power is a key physical quality of AF players (Johnston et al., 2018), as with many sports, which is developed through strength training. During pre-season, training load is predominantly accumulated through skills based training and conditioning, comprising of running sessions imbedded into training, compared to in season where there is a shift in load accumulation through matches, skills based training and upper body weight training (Ritchie et al., 2016). Lower body weight training in AF was reported to decrease during the in season phase compared to pre-season, to allow for greater recovery in the training week between matches due to the increased high speed running players are accumulating through matches therefore increasing overall total lower limb training load (Ritchie et al., 2016). Based on the evidence around the importance of recovery between matches and how strength can influence players' soreness, it is expected to observe a negative relationship between soreness scores and Champion Data© rating points. Further investigation into whether players were feeling recovered between matches is warranted, however, was not something addressed in this study. Strength training also wasn't analysed which may have been able to provide further information as to what the strength and power profiles were of the players and whether this was an influential factor over the soreness experienced by the players throughout this season.

Divulging into the second relationship identified earlier, the relationship between wellness energy scores and coaches subjective ratings states that the lower athlete's energy scores are, the lower the coaches subjectively rate their performance. Expanding on the aforementioned details around the importance of recovery, low energy can be a result of inefficient recovery between training sessions and/or matches (Kellmann, 2002, 2010). Energy levels, however, can also be influenced by other factors being more psychological in nature such as stress from training and competition (Lehmann et al., 1999). If players are feeling low on energy it is known that proceeding performances are likely going to be worse (Lehmann et al., 1999). Recovery is often considered as a physical strategy, where recovery can be passive, active or pro-active, however, recovery is also mental (Kellmann, 2010). Kellmann (2002) designed a model in which it states that recovery should be designed to work in parallel with athlete's stress levels, to keep players stress-state stable, allowing for maximal performance. Inversely, if this framework cannot be met, the inability to meet increased recovery demands can increase an individual's stress which is known to reduce performance ability (Kellmann, 2002, 2010). Alongside recovery, motivation can also play a role in players energy levels, where this motivation can come from intrinsic or extrinsic factors (Mageau & Vallerand, 2003). The most influential factor reported as being crucial to players motivation and subsequent performance, is the relationship between players and their coach, suggesting that coaches play a crucial role in influencing players mental state prior to a match (Mageau & Vallerand, 2003). Contributing to this motivation, is also an players mental toughness, whether players are able to be "mentally tough" in a match and training and withstand all of the factors encompassed by competing at the elite level (Gucciardi et al., 2008). There are multiple factors contributing to players mental toughness, however, there are two internal and two external factors identified in AF as the most influential, being lack of confidence, physical fatigue and peer/social pressures and poor playing conditions (Gucciardi et al., 2008). Players who are deemed as mentally tough demonstrate this through superior decision making, recovery from injury and consistently exhibit higher-quality performance (Gucciardi et al., 2008). Mental toughness, alongside motivation and mental recovery may be the key components to improving players' energy scores to ultimately influence positive performance outcomes, however this was not investigated in this study and may be considered in future research.

In trying to provide context around the lack of relationships identified in this study, it brings to question as to whether the appropriate tools were analysed. The GNSS metrics analysed comprised total volume, high speed running distance, sprint distance, total high intensity running distance, maximum velocity and work rate. However, acceleration is a known important measure in AF (Aughey, 2010; Johnston et al., 2015c), yet wasn't investigated in this study. In football codes, due to the congested nature of the game this can increase the number of efforts, or movements at lower intensities within small spaces, i.e., acceleration and deceleration movements (Delaney et al., 2017; Kempton et al., 2015). These movements are often completed in areas surrounding the ball in play as players are trying to gain possession of said ball (Delaney et al., 2017;

Kempton et al., 2015). Based on the knowledge that Champion Data© rating points are allocated based on players involvement in the game where majority of the categories are based on involvement with the ball i.e., field kicks, hitouts, intercepts, kick-ins, mid-chain, run and handball, shots at goal, spoils and stoppage, it could be suggested that acceleration may demonstrate a more meaningful relationship with performance compared to the metrics used in this present study.

Overall, the findings of this research failed to indicate which characteristic/s are most robust in understanding match performance in AF and did not identify a strong relationship between coaches subjective ratings and Champion Data© rating points. Two meaningful relationships were identified, however, neither provided any new information around performance, instead supported previous research around the importance of recovery between training and matches, and around the mental preparation also needed for players to perform at their best. The lack of findings also suggests alternative measures be investigated in future research, such as acceleration given being such an integral component of AF. The nil relationship between coaches subjective ratings and Champion Data© rating points suggest the two scales are measuring different things, therefore one rating system cannot be recommended over the other.

The limitations of this study revolve around the validity of the measures used for comparisons. Specifically, the wellness tool implemented is not a validated AROM therefore, cannot making meaningful inferences that wellness as a training monitoring tool has no correlation with performance. What this study was able to quantify was that the wellness questionnaire designed in house has no correlation with performance. Which may be resultant from the tool not being a validated AROM, however more research is required whereby a validated AROM should be used to eliminate this uncertainty. Secondly, Champion Data© ratings points are an objective measure whereby coaches subjective ratings as the name indicates, are a subjective measure. Despite the objective measure providing information from quantifiable actions and subjective measures being thought to be heavily influence by quantifiable actions, there was no correlation established, however, the subjective measure can be heavily biased based on the nature of collection which was not investigated through this research. Lastly, there was no meaningful relationship discovered between any of the monitoring tools i.e., GNSS, wellness and Champion Data© rating points or coaches subjective ratings suggesting that these variables cannot be used to predict performance, rather a metric more aligned with performance should be investigated in future research. Acceleration is a known important variable and as it was not investigated in study one and the metrics used proved no correlation, this suggests the need to develop better methods of quantifying volume such as potentially acceleration, driving the key aims in the proceeding studies.

CHAPTER 5. STUDY 2 – PLAYER SPEED AND ACCELERATION VOLUME DISTRIBUTION WITHIN AN AUSTRALIAN FOOTBALL COMPETITION

.5.1 Introduction

Training monitoring is commonly employed within high performance sport, with the purpose of inferring performance results or gains of players to practitioners (Ritchie et al., 2016), resultant from training adaptations carefully monitored to reduce the risk of injury, illness and fatigue (Halson, 2014). Specifically, training monitoring may indicate how players are likely to perform in competition or to reflect on how they are coping/feeling with the training program, both subjectively and objectively (Halson, 2014). Given the overwhelming volume of data that is routinely collected in high-level sport, it is good practice for practitioners to only collect data that provides meaningful information, as collecting excess data can be considered unethical (Australian Academy of Science, 2022). Global navigation satellite systems (GNSS) are one of the valid and reliable (Rampinini et al., 2015; Varley et al., 2012b) training monitoring tools used throughout amateur to elite sports. Data can be either accessed as summated reports, or individual raw data files (e.g., 10 Hz raw data). As AF is an intermittent sport, measuring total running volume does not provide an accurate representation of the intensity experienced throughout matches (Gabbett et al., 2014). Total running volume provides a number without context, whereby the speeds at which distances were accumulated at is not distinguished (Gabbett et al., 2014). Particularly in football codes, there are spatial and physical constraints that limit players reaching their maximum velocities in turn, completing movements at lower intensity within smaller spaces, placing more emphasis on acceleration and deceleration (Delaney et al., 2017; Kempton et al., 2015).

In quantifying the most intense periods of running during team sport, moving averages can be employed (Delaney et al., 2015; Delaney et al., 2017), with the literature reporting epochs ranging from one to 10 minutes (Delaney et al., 2017). Such data can be used to guide intensity in skills training (Delaney et al., 2018c). In addition to the maximal mean running speed, the distribution of running intensity over moving averages has been examined to better understand the demands of the entire match (Delaney et al., 2018a; Thornton et al., 2019). Specifically, the distribution of running can be examined by determining the volume of distance accumulated across the running speeds that occur during competition (Johnston et al., 2020). This analysis can be conducted on other metrics, such as impulse, as this can be established across the acceleration spectrum given impulse is the product of mass, acceleration and time (Johnston et al., 2020).

Acceleration is another important physical capacity to measure, as an athlete's ability to accelerate and decelerate quickly results in the rapid accumulation of high intensity workloads (Osgnach et al., 2010) and inherently positively impacts performance in regard to power output and energy cost (Ellens et al., 2022; Johnston et al., 2015c). Despite this importance, acceleration and deceleration data can be misreported based on the type of tracking technology utilised (Delves et al., 2021; Varley et al., 2017), software used (Buchheit et al., 2014) and the data filtering process (Delves et al., 2021; Varley et al., 2017). These limitations can impact the quality, reliability and validity of the data collected (Buchheit et al., 2014; Delves et al., 2021) and also the final outcomes, where research found the quantity of high-intensity efforts substantially varied depending on the data filtering process (Varley et al., 2017). A recent review noted that due to underreported methods sections, with missing information regarding methodological procedures and unclear data deriving and cleaning techniques, and a multitude of combinations between tracking technology, software, and filtering processes, it is problematic to compare literature regarding the quantification of acceleration in team sports (Ellens et al., 2022). In field-based sporting applications, Delaney et al. (2017) recommends quantifying acceleration using the absolute average acceleration as opposed to banding acceleration into counts based on pre-determined thresholds, as pre-determined thresholds can underestimate peak running demands by 20-25% (Varley et al., 2012a). To date, the volume of acceleration (impulse), has only been investigated in women's AF (Thornton et al., 2020). This research in women's AF quantified the volume of acceleration completed during pre-season training by calculating the impulse ($kN \cdot s^{-1}$) accumulated into 10% thresholds ("buckets") starting from 110-100%, working progressively down to zero (Thornton et al., 2020). Through this analysis, the greatest volume and distribution of volume was found to occur at approximately 60% of the one-minute maximal mean of match intensity, where other research conducted in AFL and rugby league found that most running demands are completed at an intensity of approximately 60% of the maximal mean (Johnston et al., 2020). Despite an abundance of research examining the maximal mean intensity in team sports (for review see Weaving et al. (2022)), there is research lacking in regards to the distribution of volume therefore, it could be suggested that there is a need to examine the volume of work accumulated across the intensity spectrum (Johnston et al., 2020).

Although distribution analyses provide practitioners with additional information compared to that of one-minute match intensity maximal means, a limitation is that the shape of the distribution is dependent on the number and size of the threshold ranges for which data is accumulated into ("buckets") in which the distance and impulse is accumulated in (Impellizzeri & Bizzini, 2012; Wilke, 2019). Aggregate methods eliminate the need for arbitrary parameter choices (i.e. "buckets" from the previous example), however are not often used outside of highly technical publications (Wilke, 2019). A type of an aggregate method is cumulative distribution, where large data sets are displayed using their distribution rather than individual data points (Wilke, 2019). This study aimed to determine the cumulative distribution of volume covered across the intensity spectrum for AF and examine the extent to which differences between level of competition (AFL vs VFL) and between match quarters (one - four).

5.2 Methods

5.2.1 Participants

Thirty-three professional AFL players (age; 24.4 ± 4.3 yr, mass; 84.9 ± 10.6 kg and stature; 189.2 ± 8.3 cm) from the same club volunteered for this study. Data were collected during 22 matches throughout the 2021 competitive season (6 wins, 16 losses). A typical training week consisted of two to three field sessions, two to three resistance training sessions and one to two additional on legs sessions consisting of either reduced volume, rehabilitation, additional conditioning, skills training depending on the individual requirements of players. Players were classified by playing position as follows: forwards (n = 8), midfielders (n = 11), backs (n = 14). The mean (± SD) observations (match files) per athlete was 15 ± 5. Ethical approval for this research project was granted by the Victoria University Human Research Ethics Committee (HRE17-138).

5.2.2 Study Design

The study design for this chapter follows that outlined in chapter 3.2.1 of this thesis where the specific data collected relevant to this study was that from matches. Of the matches, 20 were recorded using GNSS, and 2 were recorded using LPS due to playing at an enclosed stadium (Broadcaster Version 3.4.1). The specific comparisons to meet the aims of this study where; quarters and competition level. When calculating total volume and impulse within each zone, this was split into each match quarter as well as competition level.

Visual inspection of the logarithm of the cumulative volume and intensity for both distance and impulse showed a quadratic (non-linear curvilinear) relationship for quarter and game totals. To describe the distribution of distance and impulse across the intensity spectrum quadratic models were established for each player for each quarter and game.

5.2.3 Statistical Analysis

The statistical methods adopted in this chapter are outlined in chapter 3.2.2 of this thesis, whereby the specifics will be further explained. Linear mixed models were used to compare the quadratic coefficients from each model between competitions (AFL vs VFL), and match quarters (quarter 1 to quarter 4). Specifically, in these models, and either competition or quarter was entered as the predictor (fixed effect).

5.3 Results

Table 5-1 presents the coefficients for the speed distance and impulse acceleration models for the competitions (AFL and VFL) and each quarter (quarter one to four). Figure 5-1 demonstrates the distance speed model for competition level (A), and match quarters (B), showing the accumulation of distance relative to the running speed. Figure 5-2 displays the distance speed model for an individual player to provide an example of typical match data on an individual level where the players speed coefficients were; $a = 0.017$, $b = 6.6$ and $c = 271$. Figure 5-3 shows the differences between competitions and match quarters for the distance speed model coefficients (a, b and c). There were no substantial differences between the speed coefficients between competition levels. When comparing match quarters, quarter one had a very substantially higher speed a coefficient when compared to quarter four (ES = 0.40; ±90% CL = 0.17), and quarter four had a substantially higher speed b coefficient when compared to quarter one (-0.27; ±0.11). Quarter two also had a substantially higher coefficient a when compared to quarter four (0.25 ± 0.11). Figure 5-4 shows the impulse acceleration model for competition level (A) and quarters (B), demonstrating the accumulation of impulse relative to the acceleration.

Figure 5-5 demonstrates the comparisons between competition and match quarters for the impulse acceleration model coefficients (*a*, *b* and *c*). Between competition levels, VFL had a substantially higher acceleration *a* and *c* coefficients when compared to AFL (0.91; ±0.38) (0.41; ±0.14), respectively. The *b* coefficient for AFL was substantially higher than VFL (-0.75; ±0.31). When comparing match quarters, quarter four had a substantial higher acceleration *a* coefficient when compared to quarter one (0.32; ±0.14).

Table 5–1 Coefficients (*a*, *b* and *c*) for speed distance and impulse acceleration model for competition level (AFL and VFL) and match quarters (quarter one to four).

	Speed Distance Model			**Impulse Acceleration Model**		
	a	*b*	*c*	*a*	*b*	*c*
AFL	-0.02 (0.01)	6.6 (1.5)	318 (87)	-0.28 (0.09)	25.2 (5.7)	687 (73)
VFL	-0.02 (0.00)	6.6 (1.1)	332 (54)	-0.37 (0.09)	29.5 (5.9)	658 (69)
Quarter 1	-0.02 (0.01)	6.6 (2.1)	166 (134)	-0.31 (0.14)	27.2 (9.2)	514 (146)
Quarter 2	-0.02 (0.01)	6.8 (1.8)	175 (113)	-0.32 (0.12)	27.3 (7.7)	535 (119)
Quarter 3	-0.02 (0.01)	6.8 (1.9)	184 (109)	-0.34 (0.13)	28.0 (7.8)	531 (112)
Quarter 4	-0.02 (0.01)	7.2 (2.1)	165 (124)	-0.35 (0.15)	29.0 (9.0)	517 (131)

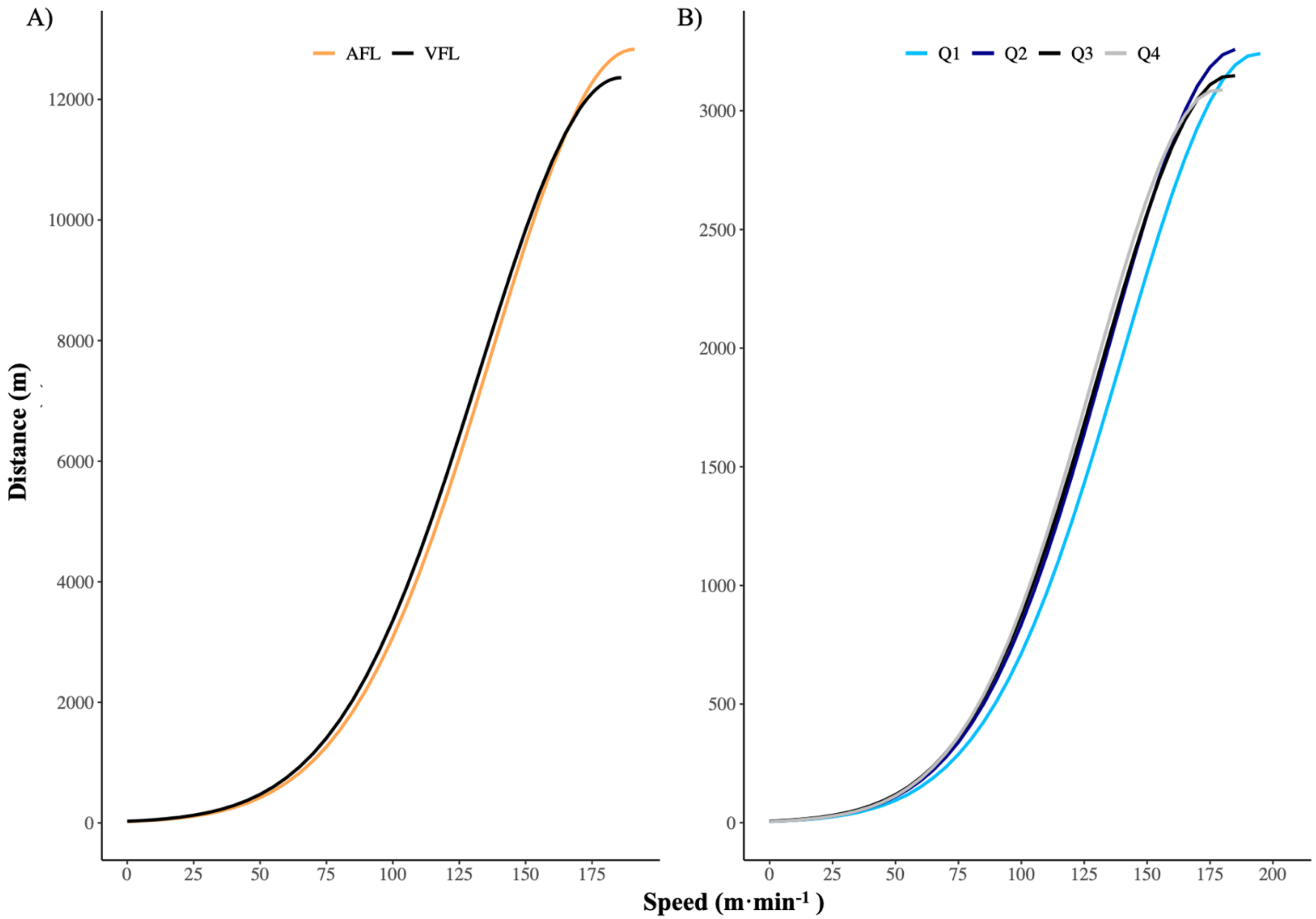

Figure 5–1 The cumulative distribution of distance in relation to speed expressed as a quadratic equation for competition level (A) and match quarters (B) in AF.

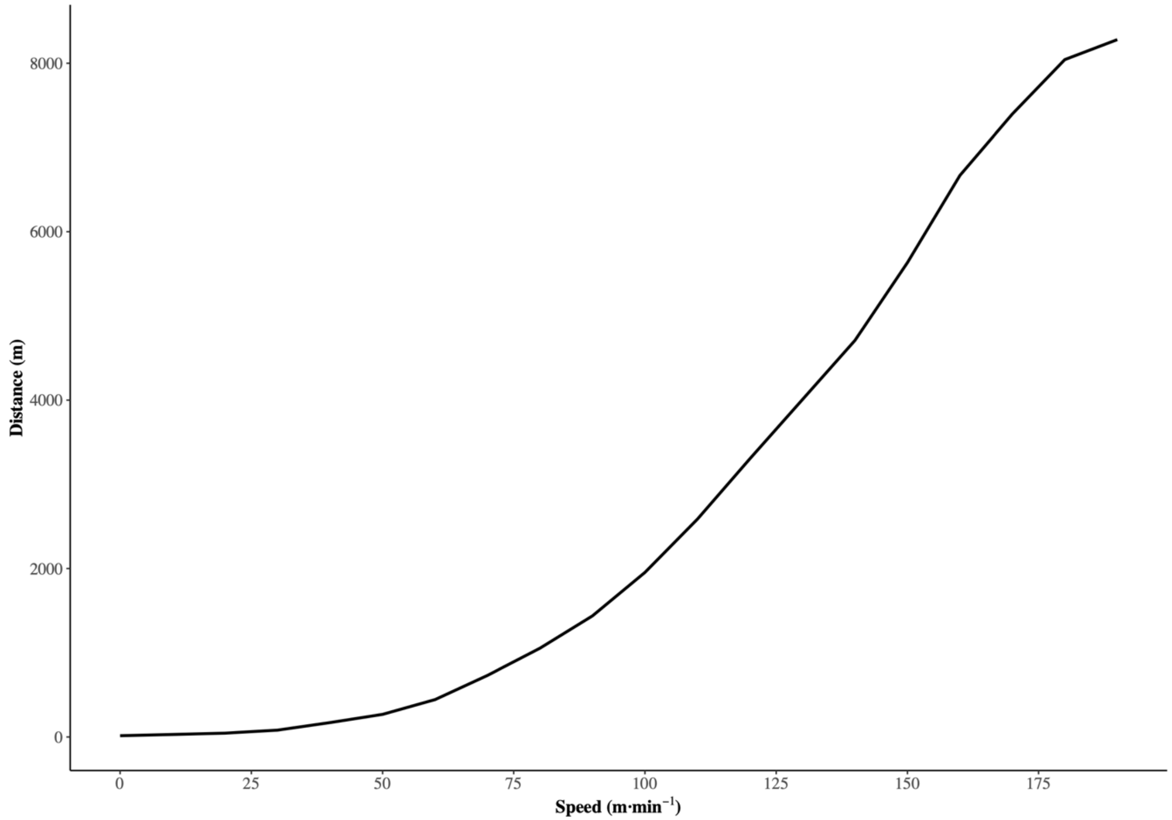

Figure 5–2 The cumulative distribution of distance in relation to speed expressed as a quadratic equation for an individual players match in AF.

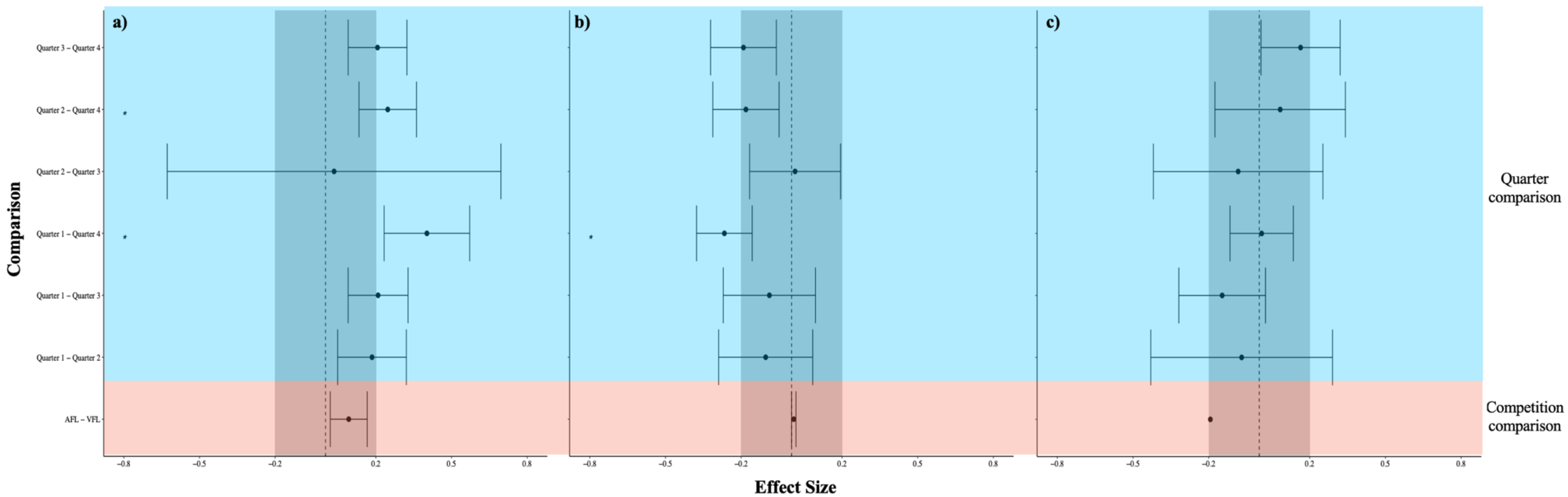

Figure 5–3 Comparison of Distance Speed Model quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between competition levels and match quarters. Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across over the shaded area (−0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES). Due to the width of the CL of the AFL vs VFL *c* coefficient comparison exceeding the width of the figure axis, the error bars have been removed for visual clarity where the value was ES = -0.21 ± 3.22.

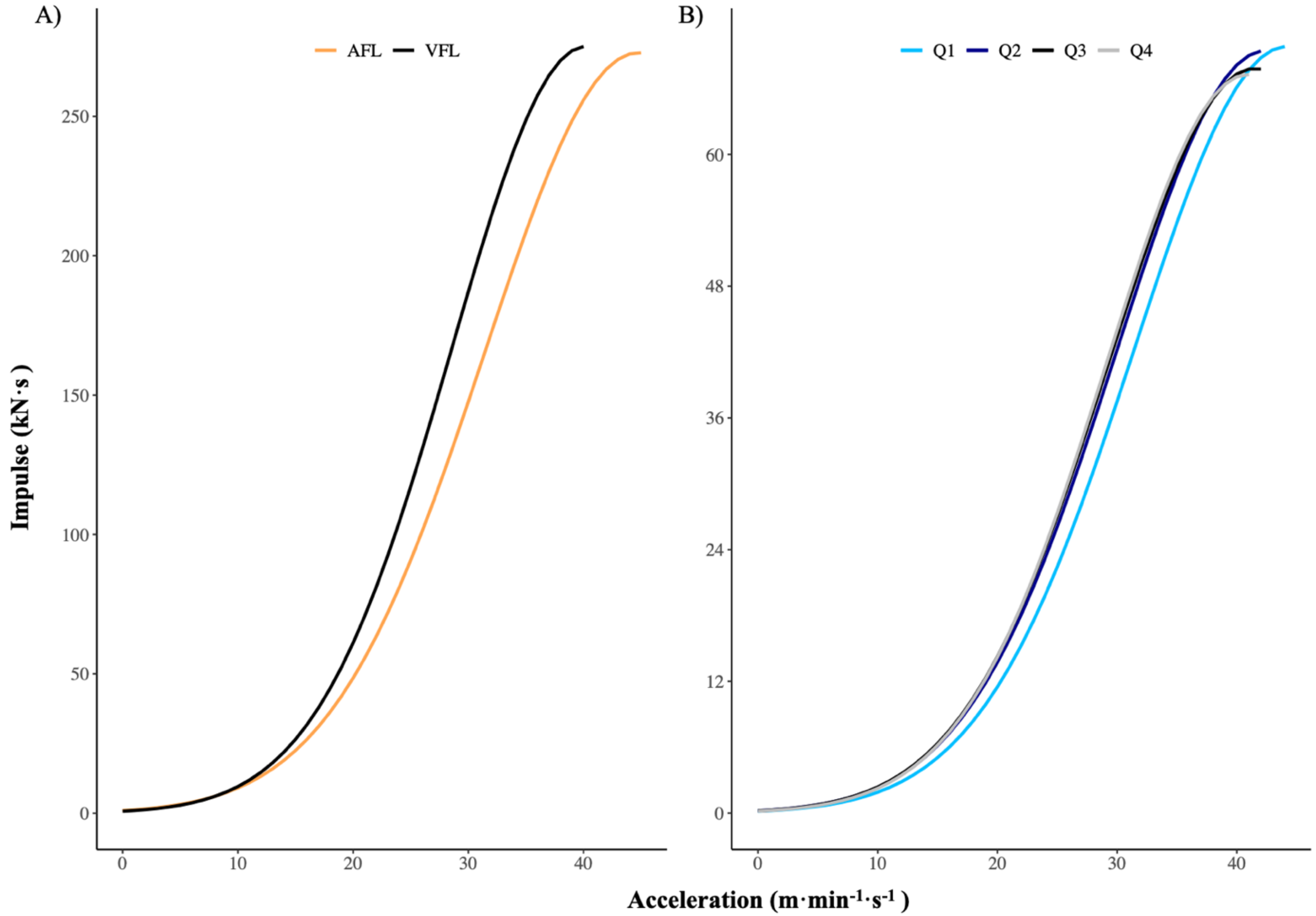

Figure5–4 The cumulative distribution of impulse in relation to acceleration expressed as a quadratic equation for competition level (A) and match quarters (B) in AF.

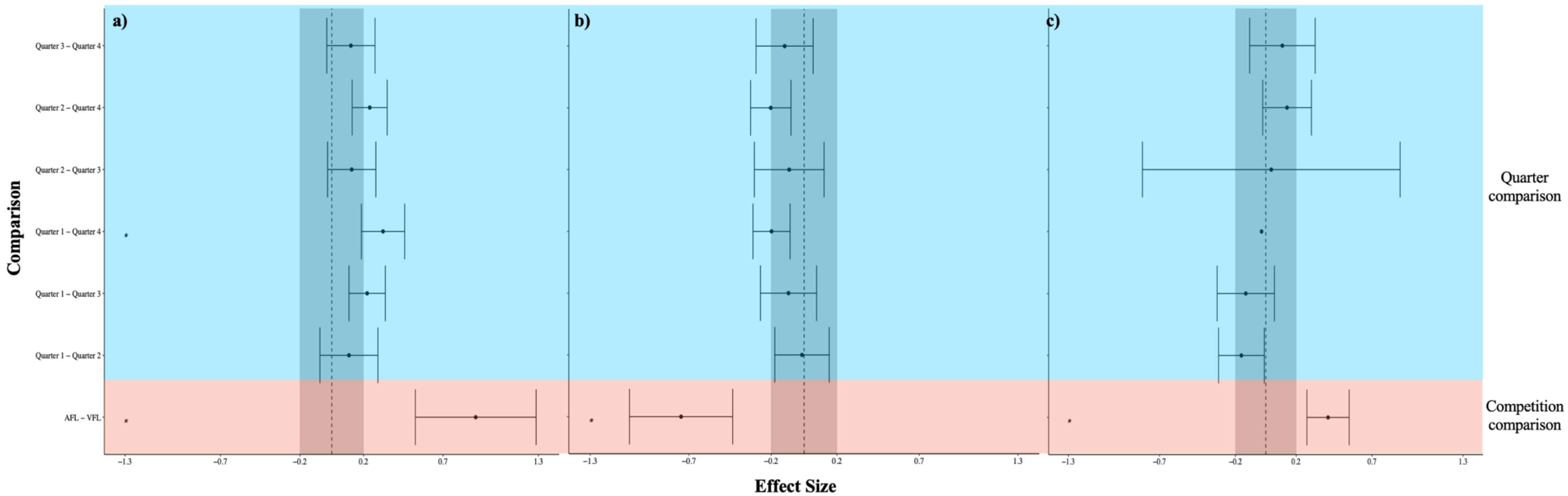

Figure 5–5 Comparison of acceleration quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between competition levels and match quarters. Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across over the shaded area (−0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES).

5.4 Discussion

The purpose of this study was to investigate the accumulation of volume across the intensity spectrum for speed and acceleration in AF matches. This study used a cumulative volume distribution to quantify running volume across the intensity spectrum, and to fit a quadratic model to the distribution to describe the shape of the distribution. Specifically, this analysis permitted the quadratic coefficients to be compared for competition levels (AFL vs VFL) match quarters for speed and acceleration demonstrating the accumulation of volume across matches and quarters. Using the quadratic coefficients, this study identified where during the match the most speed and acceleration was accumulated (first quarter), and further determined where across the intensity spectrum the competition levels (AFL and VFL) differ.

When interpreting speed, research has typically reported the total volume covered at different speed thresholds or ranges (Wisbey et al., 2010). For example, total distance (m or km), total high-speed running, total sprint distance, although these discrete measurements can limit the context of how such volume was accumulated (Gray & Jenkins, 2010). The cumulative volume method used in this study encompasses all the data into one visual (Figure 5-1a) and summaries with the coefficients for the quadratic model (Table 5-1). When interpreting Figure 5-1a, the maximal value from the y axis represents the total volume accumulated, where AFL players accumulated a greater total distance (12.8 km) compared to VFL (12.4 km), shown through the subtle shift in the line upwards, indicating a greater overall accumulation of volume. Despite this difference observed between the different competition levels, this difference is not meaningful given it is approximately 3.1% and the known meaningful difference is reported at approximately 6% (Kempton et al., 2015). Therefore, the total volume accumulated in this study is not a meaningful finding to distinguish between competition levels. The maximal value observed on the x axis represents the highest one-minute mean value for speed, that for AFL was 191 $m\cdot min^{-1}$ and VFL, 186 $m\cdot min^{-1}$, which similarly is not deemed a substantial difference. Peak one-minute speeds of AFL one-minute range from 199 – 223 $m\cdot min^{-1}$ (Delaney, 2017), however no recent research has examined this for the VFL competition. An important and practical finding of this study is that by examining the distribution, it was indicated a trend for AFL to accrue more distance compared to VFL at intensity greater than 150 $m\cdot min^{-1}$, which if simply using total match averages or maximal mean intensity to prescribe training may result in poor preparation of players. Practically, these findings suggest that VFL players transitioning into AFL should be capable to sustain accumulating distance over speeds of 150 $m \cdot min^{-1}$. This information also provides useful insight in designing skill based training drills, as it provides specific prescriptive values for practitioners to precisely plan according to (i.e., targeting >150 $m \cdot min^{-1}$ for VFL preparation), potentially resulting in players being more accustomed to the physiological demands prior to matches.

When interpreting acceleration (Figure 5-4a), the maximal value from the y-axis represents the total impulse accumulated, demonstrating VFL accumulated greater volume compared to AFL (275 kN·s and 273 kN·s respectively). This difference between competition levels however, is not a statistically significant difference therefore should not be considered as a meaningful factor when comparing AFL to VFL in reference to this study. The maximal value observed on the x-axis represents the maximal mean one-minute acceleration, demonstrating that AFL accumulated impulse at an overall higher acceleration (45 $m \cdot min^{-1} \cdot s^{-1}$) compared to VFL (40 $m \cdot min^{-1} \cdot s^{-1}$). This can further be seen through the rightward shift of the curve indicating a greater accumulation of volume at a higher intensity for AFL. As acceleration is an important physical quality for AF (Johnston et al., 2015c), this finding is of practical relevance for practitioners when aiming to prepare players for the increasing demands of the competition. When comparing the competition levels as shown in Figure 5-3, there were substantial differences in the quadratic coefficients (a, b and c). Specifically, the higher a coefficient of AFL compared to VFL reflects a narrower distribution, suggesting that impulse is accumulated within a smaller range of intensity compared to that of VFL. The b coefficient (linear component of the model) was higher for VFL, reflecting that VFL accumulated impulse earlier on the acceleration axis, thus accumulated more impulse at lower acceleration intensity. More specifically, VFL accumulated greater impulse at approximately 30 $m \cdot min^{-1} \cdot s^{-1}$, while AFL accumulated more impulse at an intensity above ~42 $m \cdot min^{-1} \cdot s^{-1}$. This is an interesting finding, as it suggests the acceleration and deceleration variables of AFL are substantially greater than what occurs in VFL. This finding also supports previous suggestions that acceleration is a key component when quantifying the running demands of team sports, given there are clear differences between competition levels.

Investigating each quarter of matches provides a more specific understanding of the accumulation of volume (speed and acceleration) throughout matches. There was a substantial difference in the speed *a* and *b* coefficient between quarter one and quarter four. Research in AFL has demonstrated that mean speeds of quarters reduce from quarter one (142 m·min^{-1}) to quarter four (130 m·min^{-1}) (Mooney et al., 2013). The present study identified that maximal mean speed reduced from 195 m·min^{-1} to 180 m·min^{-1} from quarter one to four respectively. This was also reflected through the distance accumulated dropping from 3241 m (Quarter one) to 3088 m (Quarter four), a similar decrease to previously reported values in AFL (Quarter one: 3070 ± 630 m; Quarter four: 2840 ± 630 m) (Wisbey et al., 2010). Other research in AFL has reported total difference differently where said distance it is well maintained across a match when expressed relative to duration (min) (Aughey, 2010). It is hard to determine the cause given research has suggested there is no difference in total distance due to conditioning level, team ranking in the competition (i.e. higher vs lower on the competition ladder) or physical capabilities (Aughey, 2010). Where other research in AFL, suggested the decline in total volume throughout the match was likely resultant from fatigue accumulating from higher physical demands in the early stages of the game (Coutts et al., 2010). This is supported by the substantial difference (quarter one and quarter four) shown in the present study, displayed by the leftward shift in the curve in Figure 1b.

Following the same pattern as speed, the impulse acceleration model had a substantial difference in the *a*, *b* and *c* coefficients between quarter one and four. The difference was reflected with quarter one having a greater impulse (70 kN·s) when compared to quarter four (67 kN·s). Further, the maximal mean absolute acceleration was 44 m·min^{-1}·s^{-1} in quarter one and 41 m·min^{-1}·s^{-1} in quarter four. The substantial difference in coefficient *a* (Figure 5-5), resulted in a narrower distribution shape, where a greater accumulation of volume occurred at higher intensity quarter one (Figure 5-4b). When combining these results for both distance and speed, it further supports the concept of fatigue contributing to the progressive reduction in intensity throughout the course of matches (Coutts et al., 2010; Wisbey et al., 2010).

Overall, the findings of this research indicate that there are differences in speed and acceleration between competition levels and match quarters. This study has presented a novel method to quantify the volume and intensity of running that occurs in AF, that has important practical applications for those preparing AF players for competition. By using a cumulative distribution, this method allows a visual representation of all the entire match file data as opposed to summating values in pre-determined thresholds. The visual representation outlines clear intensity and volume that practitioners can consider in their training prescription. Whether it be replicating match demands in training or exposing sub-elite players to elite levels to prepare them if they are trying to improve their performance. The analysis highlighted that acceleration appears to be an important variable differentiating the competition levels, due the substantial difference between competition levels, where AFL accumulated impulse at higher intensity then VFL. Further, the accumulation of volume for both speed and acceleration appeared to decline between quarter one to four. More volume was accumulated at higher intensity and overall total volume and speed in the first quarter when compared to the fourth, suggesting an accumulation of fatigue over the course of matches.

The limitation highlighted in this study is the difference in observations between the AFL and VFL competition, there was a much smaller sample size for the VFL observations given there are less players in this cohort compared to the AFL cohort. In doing so, a smaller sample size provides less variety in responses therefore the differences observed could be partly resultant from a small sample size. Future research should endeavour to investigate a large cohort, either multiple clubs or multiple seasons to have more equivalent observations to further enhance and support the findings found in this study to confirm that the differences observed are true differences across competition levels and not resultant from sample size and number of observations recorded.

CHAPTER 6. STUDY 3 – SPEED AND ACCELERATION DISTRIBUTION ACROSS AN AFL PRE SEASON

6.1 Introduction

The overall aim of periodisation is to elicit a physiological response caused by an exercise stimulus, resulting in adaptation leading to an enhancement of performance (Bompa & Haff, 2009). Using a periodisation model, preparation for competition or major events can be separated into phases, whereby the focus or aim of training changes (Bompa & Haff, 2009). The preparatory phase (also known as 'pre-season' in team sports), is designed to maximise physical adaptations of players in preparation for the upcoming competitive phase. In the elite men's Australian football competition (AFL), the pre-season phase typically extends from November through to February (Moreira et al., 2015; Ritchie et al., 2016). The pre-season phase can be further categorised into mesocycles that are approximately four to six weeks in duration (Bompa & Haff, 2009; Moreira et al., 2015; Ritchie et al., 2016). In AFL, these mesocycles fall into a 'pre-Christmas', 'post-Christmas' and 'pre-competition' time periods, where a shift in the prescription of training occurs (Buchheit et al., 2015).

In the AFL pre-season, the three mesocycles can alternatively be referred to as the general preparation (pre-Christmas), specific preparation (post-Christmas) and pre-competition phase. During the pre-Christmas phase, the aim is to develop general fitness with a focus on high volume and lower intensity (Moreira et al., 2015). Throughout the post-Christmas phase, there is an increased prescription of high-intensity technical and tactical drills and more drills designed to simulate or exceed match intensity (Ritchie et al., 2016). The pre-competitive phase is a period where practice matches are scheduled, and the focus is high intensity with reduced volume (Moreira et al., 2015). During the pre-competitive phase there is an increased focus on recovery and rejuvenation in preparation for competition (Slattery et al., 2012). Within individual AF training sessions there are various drills completed, ranging from low to high intensity consisting of warm-ups, fundamental skills such as ball handling, kicking, handballing and marking, small-sided games, full ground simulated match drills, conditioning, and game development drills (Moreira et al., 2015; Ritchie et al., 2016). Each drill is completed at varied intensity and volume depending on the aim of the drill, which is further specific to the phase and the time (Moreira et al., 2015; Ritchie et al., 2016). It is known that the pre-Christmas phase accumulates greater distances at a lower intensity (Farrow et al., 2008) compared to the post-Christmas phase where the training prescribed is often at a higher intensity and pre-competition where training volume is decreased (Ritchie et al., 2016). Despite knowing these differences between phases, the distribution of speed and intensity across training is still unknown.

Throughout a training session various metrics change based on the drill being prescribed where distance (m), speed ($m \cdot min^{-1}$) and acceleration ($m \cdot min^{-1} \cdot s^{-1}$) are deemed the most important given their inherent influence on athletic ability (Johnston et al., 2018; Sullivan et al., 2014). Understanding how distance, speed and acceleration accumulate across the duration of training would assist practitioners in understanding the volume and intensity achieved in different drill types to aid in training prescription and design. To quantify this accumulation of speed and acceleration, large data sets with continual data points are beneficial given they eliminate the need for averaging or summating data points.

Aggregate methods can provide more information as to the accumulation across the duration of a training session given this analysis would incorporate datapoints from the entire duration and encompass more data (Wilke, 2019). Cumulative distribution, is a type of aggregate method which can show the distribution of training volume, which utilises the whole data set instead of individual data points (Wilke, 2019). Through this analysis, it is possible to gather clear information about the distribution of speed and acceleration across the different training drill types, which is yet to be examined in a sporting context. Where understanding the distribution of speed and acceleration can assist practitioners by providing in depth information around volume and intensity for each training drill modality. Therefore, the aim of this study was to examine the cumulative distribution of volume during the pre-season phases and training drill modalities in AF.

6.2 Methods

6.2.1 Participants

Forty-three professional AFL league players (age; 24.4 ± 4.3 yr, mass; 84.0 ± 10.3 kg and stature; 189.0 ± 7.9 cm) from the same club volunteered for this study. Data was collected over the 2022 AFL season pre-season period running from November 2021 through to

March 2022. The typical training week for players consisted of 2-3 field sessions, 2-3 resistance sessions and 1-2 additional training sessions completed on field consisting of either reduced volume, rehabilitation, additional conditioning, skills training depending on the individual requirements of players. Players were classified by playing position as follows: forwards (n = 13), midfielders (n = 14), backs (n = 16). The mean (± SD) number of observations per player was 29 ± 3. Ethical approval for this research project was granted by the Victoria University Human Research Ethics Committee (HRE17-138).

65.2.2 Study Design

The study design for this chapter follows the details introduced in chapter 3.2.1 of this thesis where the specific data collected relevant to this study was that from training sessions conducted throughout the pre-season.. The pre-season phase was further split into three different subphases; "pre-Christmas" was any training session completed from the beginning of pre-season to the Christmas break in December 2021. The "post-Christmas" phase was the training sessions from the return after Christmas break in January to the commencement of practice games in February. The final phase was the "pre-competition" phase including the training sessions from the commencement of the practice games up until Round 1 of the 2022 AFL Premiership season in March.

Training drills were split pre-training into different categories based on the estimated work rate ($m \cdot min^{-1}$) of the given drill. The different categories were; warm up (active stretches, movement activations, light jogging, basic skill work), fundamentals ($<70\ m \cdot min^{-1}$) comprised of drills that focus on the basic skills of the game completed at a low work rate i.e. slow paced handball drills, tackling drills, kicking in partners/groups, structure ($70 – 128\ m \cdot min^{-1}$) comprised of football specific drills completed at a higher work rate i.e. kicking drills completed down the length of the field of play, high intensity handball drills, game plan ($>128\ m \cdot min^{-1}$) comprised of high intensity match simulation drills or small sided games and conditioning being any running work without the use of a football. For the analysis of this study, warm up and rehabilitation drills were excluded from the analysis. The total volume of distance and impulse in each zone across each pre-season phase, and training drill modality was calculated. The cumulative volume was then established relative to intensity for each variable.

Visual inspection of the logarithm of the cumulative volume and intensity for both distance and impulse showed a quadratic (non-linear curvilinear) relationship for pre-season phase and training drill modality totals. To describe the distribution of distance and impulse across the intensity spectrum quadratic models were established for each player for each phase and drill modality.

6.2.3 Statistical Analysis

The statistical procedure used in this chapter are detailed in chapter 3.2.2 of this thesis, where the specific details relative to the aims of this study will be discussed following. Linear mixed models were used to compare the quadratic coefficients from each model between pre-season phase (pre-Christmas, post-Christmas and pre-competition), and training drill modality (fundamentals, structure and game plan). Specifically, phase or drill modality was entered as the predictor (fixed effect).

6.3 Results

Table 6-1 presents the coefficients for the speed distance and impulse acceleration models for the different pre-season phases (pre-Christmas, post-Christmas and pre-competition) and training drill modalities (fundamentals, structure, game plan and conditioning).

Figure 6-1 depicts the absolute and relative distance accumulated between pre-season phases for the different drill modalities. It should be noted that for the relative plots a shift to the right indicates a greater accumulation of volume at higher speeds. Figure 6-2 shows the comparisons between pre-season phases and training drill modalities for the distance speed model coefficients (*a*, *b* and *c*). Post-Christmas had substantially higher *a* and *c* coefficients compared to pre-competition (ES = 0.35; ±90% CL = 0.15, 0.53 ± 0.22, respectively). In comparison, the *a* and *c* coefficients were substantially lower in pre-competition compared to pre-Christmas (-0.35; ±0.15, -0.63 ± 0.27 respectively). Coefficient *b* was substantially lower in post-Christmas compared to pre competition (-0.35; ± 0.15) and higher in pre-competition compared to pre-Christmas (0.45; ± 0.19). The *a* coefficient was substantially lower in fundamental compared to game plan and structure drills (-0.80 ± 0.34 and -2.02 ± 0.85, respectively) and substantially lower in game plan drills compared to structure drills (-0.48 ± 0.20).

Table 6–1 Coefficients (*a*, *b* and *c*) for speed distance and impulse acceleration model for pre-season phases (pre-Christmas, post-Christmas and pre-competition) and training drill modalities (fundamentals, structure, game plan and conditioning). Where fundamental drills are focused on basic skills of the game completed at low intensity (<70 m·min^{-1}), structure drills being football specific drills completed at a higher intensity (70 – 128 m·min^{-1}), game plan being high intensity match simulations or small sided games and conditioning being any running drills without the use of a football.

	Speed Distance Model			**Impulse Acceleration Model**		
	a	*b*	*c*	*a*	*b*	*c*
Pre-Christmas	-0.027 (0.017)	8.2 (2.8)	172 (132)	-0.416 (0.220)	32.4 (11.2)	520 (166)
Post-Christmas	-0.028 (0.012)	8.5 (2.2)	157 (136)	-0.426 (0.202)	32.9 (10.3)	522 (141)
Pre-competition	-0.032 (0.015)	9.4 (2.6)	71 (181)	-0.450 (0.314)	33.1 (12.4)	475 (165)
Fundamentals	-0.040 (0.010)	10.2 (1.7)	204 (85)	-0.525 (0.250)	36.8 (9.7)	544 (108)
Structure	-0.022 (0.007)	7.6 (1.6)	217 (128)	-0.455 (0.163)	33.8 (8.3)	559 (131)
Game plan	-0.029 (0.017)	9.0 (2.9)	78 (160)	-0.403 (0.199)	32.4 (11.2)	472 (164)
Conditioning	-0.021 (0.014)	7.6 (2.6)	47 (148)	-0.312 (0.269)	27.6 (12.9)	455 (188)

Coefficient *a* was substantially higher in conditioning drills compared to fundamental and game plan drills (1.55 ± 0.65 and 0.47 ± 0.20, respectively). Coefficient *b* was substantially higher in fundamental drills compared to game plan and structure drills (0.50 ± 0.21 and 1.54 ± 0.65, respectively) and higher in game plan drills compared to structure drills (0.57 ± 0.24). Conditioning drills were substantially lower compared to fundamental and game plan drills for coefficient *b* (-1.15 ± 0.49 and -0.49 ± 0.20, respectively). For *c* coefficients, fundamental drills were substantially higher than game plan (0.98 ± 0.41) and game plan drills were substantially lower than structure drills (-0.95 ± 0.40). Conditioning drills were substantially lower than fundamental and structure drills for coefficient *c* (-1.31 ± 0.55 and -1.23 0.52, respectively).

Figure 6-3 shows the absolute and relative impulse accumulated between pre-season phases for the different drill modalities. It should be noted that for the relative plots a shift to the right indicates a greater accumulation of volume at higher acceleration. Figure 5-4 shows the comparisons between pre-season phases and training drill modalities for the impulse acceleration model coefficients (*a*, *b* and *c*). The *c* coefficient was substantially higher in post-Christmas compared to pre-competition (0.31 ± 0.13) and substantially lower in pre-competition compared to pre-Christmas (-0.27 ± 0.11). The *a* coefficient was substantially lower in fundamental drills compared to game plan and structure drills (-0.54 ± 0.23 and -0.33 ± 0.12, respectively); and substantially higher in game plan drills compared to structure drills (0.29 ± 0.15). Conditioning drills were substantially higher than fundamental, game plan and structure drills for coefficient *a* (0.82 ± 0.35, 0.38 ± 0.16 and 0.64 ± 0.27, respectively). Fundamentals drills were substantially higher for coefficient *b* compared to game plan and structure drills (0.42 ± 0.18 and 0.33 ± 0.13, respectively). Conditioning drills were substantially lower compared to fundamental, game plan and structure drills for coefficient *b* (-0.80 ± 0.34, -0.40 ± 0.17 and -0.57 ± 0.24, respectively). Lastly, coefficient *c* was substantially higher in fundamental drills compared to game plan drills (0.52 ± 0.22) and substantially lower in game plan drills compared to structure drills (-0.59 ± 0.25). Coefficient *c* was also lower for conditioning drills when compared to fundamental and structure drills (-0.58 ± 0.25 and -0.64 ± 0.27, respectively).

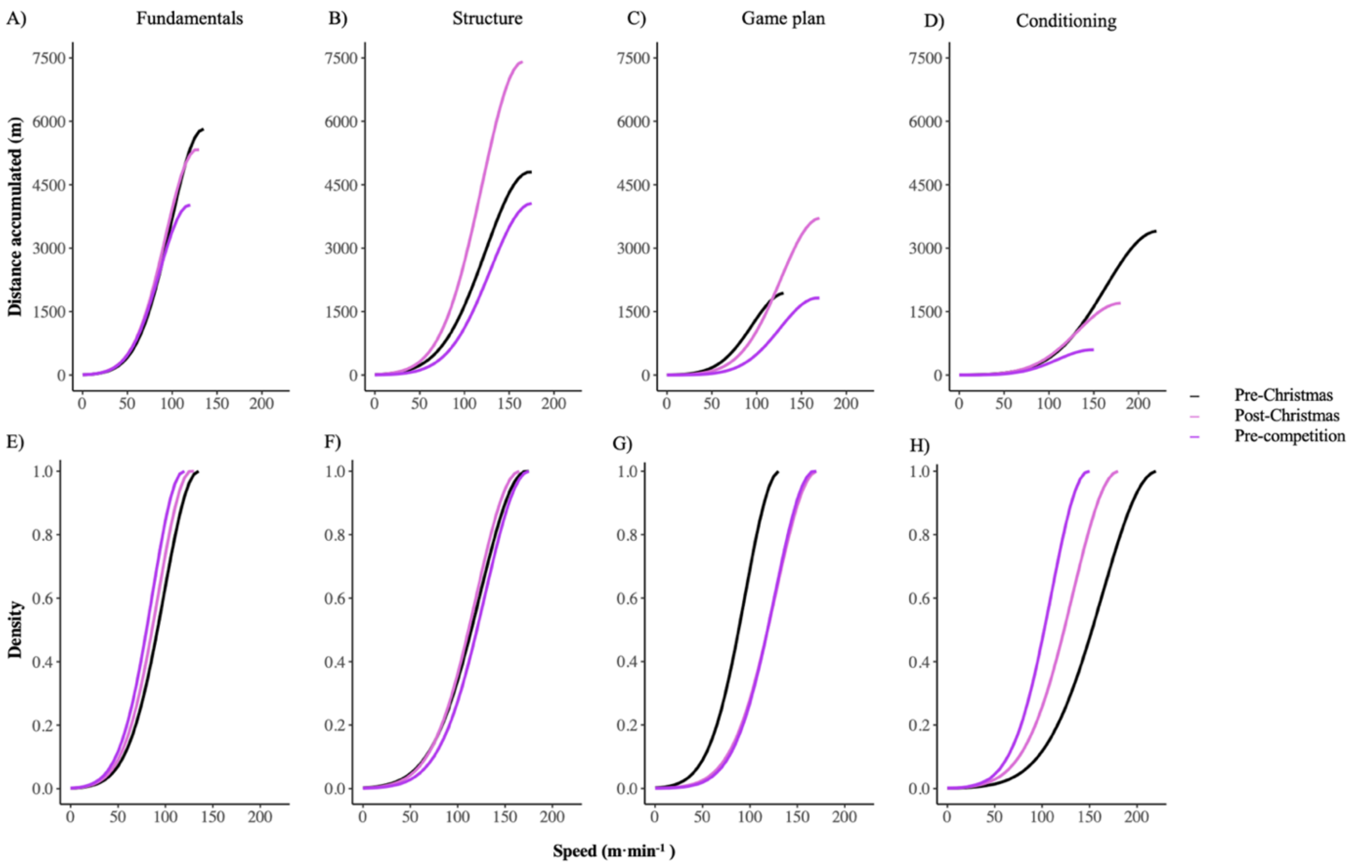

Figure 6–1 The cumulative distribution of distance in relation to speed expressed as a quadratic equation for all pre-season phases and training drill modalities (fundamentals, structure, game plan and conditioning) displaying absolute distance (top panels) and relative distance (bottom panels) in AF. Where fundamental drills are focused on basic skills of the game completed at low intensity (<70 m·min^{-1}), structure drills being football specific drills completed at a higher intensity (70 – 128 m·min^{-1}), game plan being high intensity match simulations or small sided games and conditioning being any running drills without the use of a football.

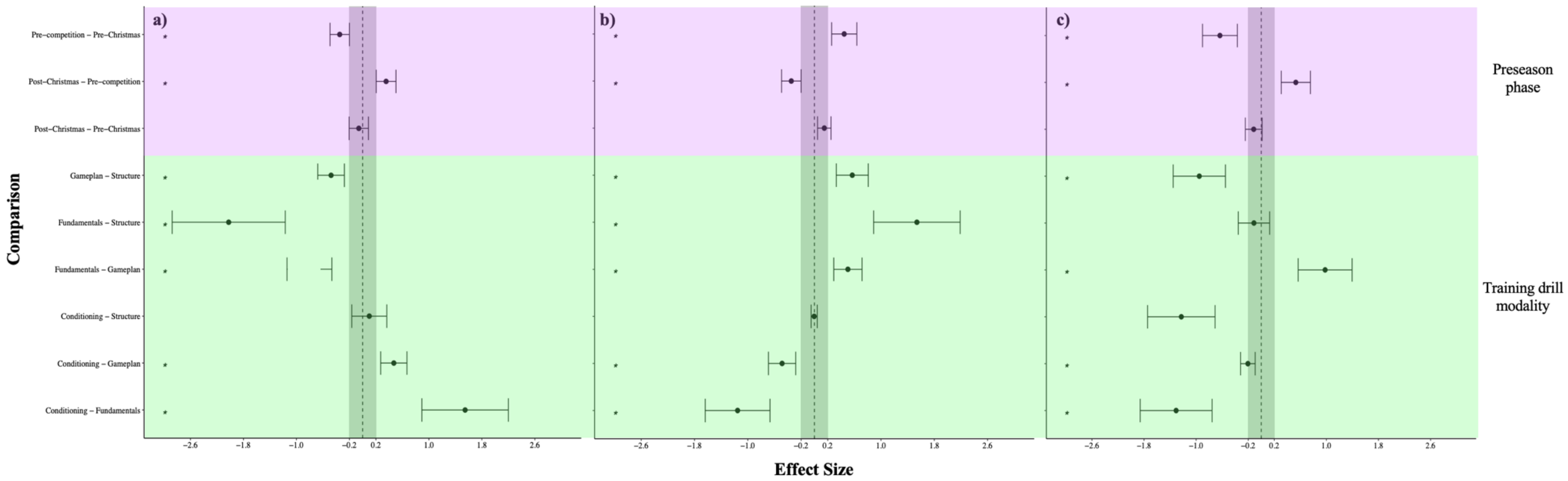

Figure 6–2 Comparison of speed quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between pre-season phases and training drill modalities (fundamentals, structure, game plan and conditioning). Where fundamental drills are focused on basic skills of the game completed at low intensity (<70 m·min^{-1}), structure drills being football specific drills completed at a higher intensity (70 – 128 m·min^{-1}), game plan being high intensity match simulations or small sided games and conditioning being any running drills without the use of a football. Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across the shaded area (– 0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES).

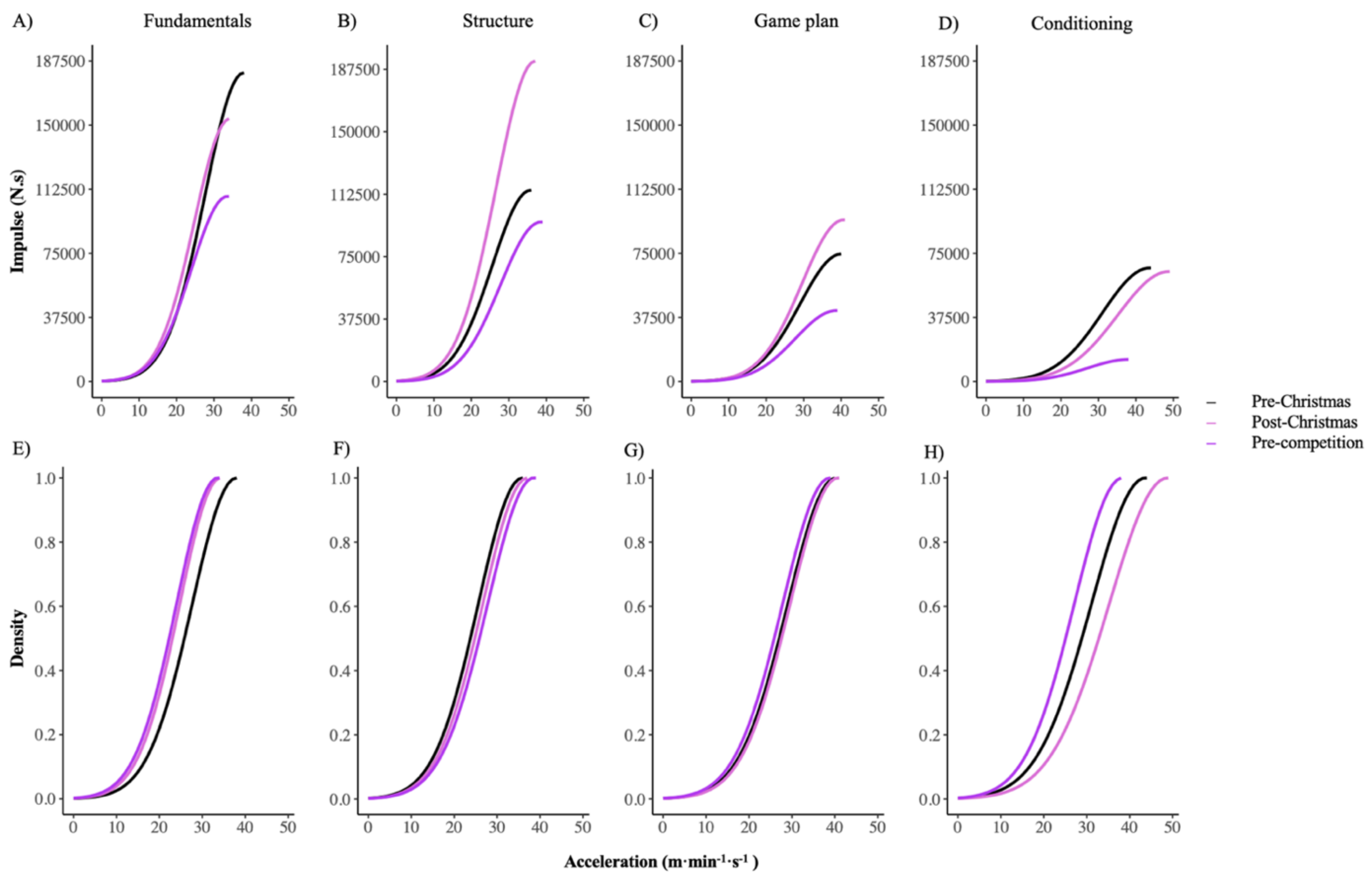

Figure 6–3 The cumulative distribution of distance in relation to acceleration expressed as a quadratic equation for all pre-season phases and training drill modalities (fundamentals, structure, game plan and conditioning) displaying absolute impulse (top panels) and relative impulse (bottom panels) in AF. Where fundamental drills are focused on basic skills of the game completed at low intensity (<70 m·min^{-1}), structure drills being football specific drills completed at a higher intensity (70 – 128 m·min^{-1}), game plan being high intensity match simulations or small sided games and conditioning being any running drills without the use of a football.

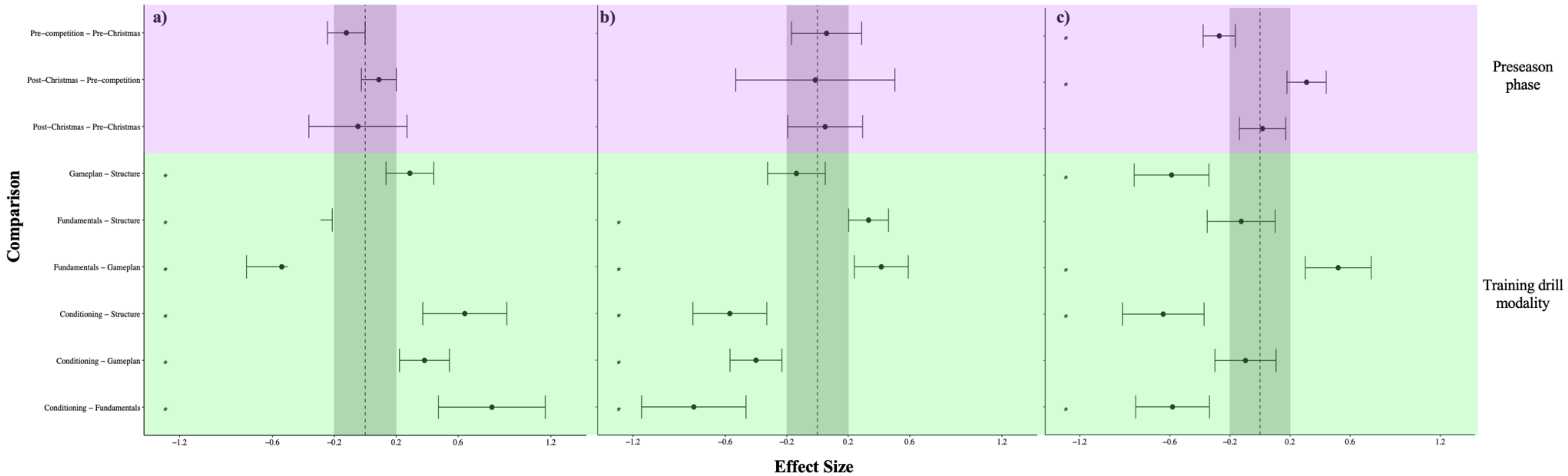

Figure 6–4 Comparison of acceleration quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between pre-season phases and training drill modalities (fundamentals, structure, game plan and conditioning). Where fundamental drills are focused on basic skills of the game completed at low intensity (<70 m·min^{-1}), structure drills being football specific drills completed at a higher intensity (70 – 128 m·min^{-1}), game plan being high intensity match simulations or small sided games and conditioning being any running drills without the use of a football. Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across the shaded area (– 0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES).

6.4 Discussion

This study investigated the accumulation of volume across the intensity spectrum for speed and acceleration throughout an AF pre-season and compared the different pre-season phases and training drill modalities. The cumulative volume distribution used in this study showed a clear difference between the different pre-season phases where the post-Christmas phase accumulated the greatest speed. When further investigating this phase, post-Christmas structure drills accumulated the greatest weekly total distance (7.4 km). Structure drills also accumulated the greatest weekly distance within the pre-competition phase being 4.1 km. During the pre-Christmas phase, the greatest weekly volume is accumulated during fundamental drills (5.8 km). Fundamental drills accumulating the greatest volume during the pre-Christmas phase is expected given the nature of the pre-Christmas phase and the training drill modality. The pre-Christmas phase is focused on low intensity, high-volume training and basic tactical skills (Bompa & Haff, 2009; Farrow et al., 2008; Moreira et al., 2015; Ritchie et al., 2016), where fundamental drills are those targeted at developing these basic tactical skills. For the post-Christmas and then pre-competition phase, training intensity is expected to increase (Moreira et al., 2015; Ritchie et al., 2016) which is seen here with greater volume accumulating in game plan drills which are designed as the highest intensity drills (>128 $m \cdot min^{-1}$). There is also decreased weekly volume from conditioning drills across the phases, where pre-Christmas accumulates 3.4 km, decreasing to 1.7 km and 0.5 km though post-Christmas and pre-competition respectively. There is a clear shift towards more skills-based training as the phases progress whereby this volume is taken away from conditioning drills therefore explaining this reduction in volume. These findings are expected given, periodisation states low intensity training volume will decrease over the pre-season with an increased development of higher intensity training volume and more skill-based development (Bompa & Haff, 2009; Farrow et al., 2008).

Pre-Christmas conditioning drills were completed at the highest one-minute speed maximal mean of all of the training drill modalities across all pre-season phases being 220 $m \cdot min^{-1}$. The pre-Christmas phase accumulated the highest intensity of the pre-season compared to all four training drills modalities. However, when excluding conditioning drills and only analysing skill-based drills only, post-Christmas had the highest intensity, indicating conditioning drills significantly contribute to the distribution of volume and intensity across the pre-season. Conditioning drills within football codes, accumulate high speeds given the nature of the drills are designed to elicit high work-rates to prepare players for the speed demands of competition where reported conditioning drills in soccer were designed in improving repeat effort ability (Ade et al., 2014) and in rugby league targeted at maximal aerobic speed running (Gabbett & Godbolt, 2010). Repeated effort ability and maximal aerobic speed running have proven to improve through AF specific conditioning drills that are designed by the clubs high performance practitioners (Corbett et al., 2017). Given conditioning drills are running based and do not account for game scenarios, change of direction and decision making it can be easier to accumulate higher speed given the one-dimensional structure (Gabbett, 2006b). When drills were focused on game scenarios, incorporating change of direction and decision making the highest one-minute mean was reduced to 175 $m \cdot min^{-1}$ which was achieved in pre-Christmas and pre-competition structure drills.

By examining the distribution of the speed distance model, there is a clear reduction in speed and weekly volume for fundamental and conditioning drills as the pre-season progresses. This reduction in speed could be attributed to the prescription of training when following a periodisation model as prescribed by the high-performance manager for the club from which this current study was analysing. Where there is a shift between longer, high volume conditioning at the beginning of pre-season and shorter, high intensity-based drills closer towards competition (Bompa & Haff, 2009; Gabbett & Godbolt, 2010). This reduction in speed and volume can be explained with the decreased intensity focus of conditioning and fundamental drills as the pre-season progress, where these drills are completed at a reduced capacity. Fundamental drills accumulate less volume given there is less training time dedicated to these drill types and more time dedicated to structure and game plan drills, evident from the increased weekly volume for both structure and game plan drills into the post-Christmas phase. This shift in training prescription is also evident through the total weekly volume where the post-Christmas phase had the highest weekly distance accumulated (18.1 km) compared to pre-Christmas (15.9 km) and lastly, pre-competition (10.4 km).

Across all pre-season phases, the greatest impulse was accumulated during post-Christmas (505 $kN \cdot s$), followed by pre-Christmas (437 $kN \cdot s$) and lastly pre-competition (259 $kN \cdot s$). Further analysing training drill modalities, post-Christmas conditioning drills accumulated impulse at an overall higher acceleration of 49 $m{\cdot}min^{-1}{\cdot}s^{-1}$. Despite this, post-Christmas game plan drills accumulated greater impulse at an acceleration of 41 $m{\cdot}min^{-1}{\cdot}s^{-1}$, being the highest achieved for skills-based training. This can further be seen through the rightward shift of the curve, indicating greater accumulation of volume for conditioning and game plan drills, specifically from the post-Christmas phase. These findings are novel, given no previous research has analysed acceleration in $m{\cdot}min^{-1}{\cdot}s^{-1}$ and further the distribution of this acceleration. Research has reported acceleration in regard to total acceleration efforts (Wisbey et al., 2010) or acceleration load (Thornton et al., 2022), which are not comparable to the acceleration measured in this study.

Acceleration is a known important physical quality for AF (Aughey, 2010; Johnston et al., 2015d), therefore understanding which drill types elicit these high rates of acceleration can assist practitioners when preparing players for the demands of AF. Fundamental drills have the lowest acceleration for post-Christmas and pre-competition. The low acceleration is unsurprising, given fundamental drills are designed to be of the lowest intensity of the three training drill modalities. During the pre-Christmas phase, fundamental drills have a higher acceleration 38 $m{\cdot}min^{-1}{\cdot}s^{-1}$, however, this could be proportional to the amount of time spent completing these drills, given pre-Christmas had the greatest volume accumulated in fundamental drills.

There were substantial differences in the quadratic coefficients (*a, b* and *c)*, specifically, the higher coefficient *a* of fundamentals compared to game plan, structure and conditioning drills reflects a narrower distribution, suggesting that impulse is accumulated within a smaller range of intensity compared to game plan, structure and conditioning drills. The narrow distribution of impulse for fundamental drills makes sense given fundamental drills were designed in much smaller field sizes than those of game plan and structure drills which often utilise a half to full field and conditioning drills which are typically long distance open-field designs. Fundamental drills will inherently have smaller areas to generate larger acceleration, and given fundamental drills are low intensity skill-based drills, a lower acceleration is expected. The present study found in fundamental drills, acceleration ranged between 34 -38 $m{\cdot}min^{-1}{\cdot}s^{-1}$ where gameplay drills ranged from 39 - 41 $m{\cdot}min^{-1}{\cdot}s^{-1}$, structure drills 36 - 39 $m{\cdot}min^{-1}{\cdot}s^{-1}$ and conditioning drills 38-49 $m{\cdot}min^{-1}{\cdot}s^{-1}$. The *b* coefficient (linear component of the model) was higher for fundamental drills, reflecting these drills accumulated impulse earlier on the acceleration axis, therefore accumulating impulse at lower acceleration intensity. Fundamental drills accumulated the lowest acceleration and impulse out of all drill modalities, demonstrating fundamental drills are the least intense drills, while game plan are the most intense skills-based which supports the design and categorisation of these drills in their existing training prescription. Despite these findings being substantial the shift in the curves for the acceleration impulse model are visually less clear when compared to the speed distance models, suggesting that this increase in intensity is resultant from an increase in higher speed running, as opposed to greater acceleration and deceleration efforts.

Overall, the findings of this research indicate that there are substantial differences in speed and acceleration between pre-season phases and training drill modalities supported by the design of periodisation and the goal for each pre-season phase. This study has presented a newly developed method introduced in Chapter 5 of this thesis, to quantify the volume and intensity of running that occurs in an AF pre-season, that has important practical applications for those preparing training sessions for AF players. Through using a cumulative distribution, there was a visual representation of entire pre-season training files as opposed to summating values in pre-determined thresholds. The analysis demonstrated that acceleration is an important variable differentiating between training drill modalities, due to the substantial differences between drills, where conditioning drills accumulated greater impulse than fundamental, structure and game plan drills. Where game plan drills accumulated the greatest amount of impulse at higher intensity. This suggests that when periodising their training performance staff should incorporate conditioning drills if they are seeking to achieve absolute maximal acceleration, or game plan drills if they are wanting a skills-based drill that will accumulate a large amount of acceleration at a higher intensity. Further, the post-Christmas phase accumulated the largest amount of volume, whilst still maintaining a high intensity. These findings support the use of different training drill modalities which can be implemented and manipulated to meets the demands of each pre-season phase following the guidelines of periodisation. Despite this study being completed during a pre-season phase, it has transferable qualities to both pre-seasons and in-season phases in regard to periodisation. These findings can assist in regard to periodisation within an in-season phase as the results provide insight as to which training drill modalities are catered towards providing greater overall volume (structure), the greatest intensity (conditioning drills) and also how conditioning vs skill-based training drill modalities differ (highest intensity achieved in drills that are open plan, no decision making i.e., conditioning vs closed areas with decision making and strategy i.e., game plan drills). Based on the capacities the practitioner wants to develop/focus on based a match day turnaround and the availability of training sessions, training can then be designed based on what each type of training drill modality elicits.

The limitations of this study include the descriptive nature whereby training drills were classified into their various modalities being; fundamentals, structure, game plan and conditioning. Conditioning drills are relatively well reported in the literature and easily comparable, whereas the skills-based training modalities are harder to correlate given the thresholds identified the categorise the training drills were determined by the club practitioner. Therefore, the classification is highly specific to the AFL club used for this research which can pose a challenge for external practitioners to relate their findings to. Despite the training drill classification used there is still large variation amongst training drills as each drill offers a different training stimulus, where future research should seek to explore the distribution of training and the subsequent training effects of the varying stimuli.

CHAPTER 7. STUDY 4 – INVESTIGATING THE EFFECTS OF MATCH TURNAROUND LENGTH ON SPEED AND ACCELERATION OVER AN AFL SEASON

7.1 Introduction

Performance is the result of fitness, minus fatigue (Calvert et al., 1976), whereby periodised training can improve players fitness and reduce fatigue (Borresen & Lambert, 2009). The concept of periodisation and how training stimulus is manipulated can be drawn from the previous chapter (Chapter 6). Depending on the sport, training is either designed around a major competition i.e. swimming, or a more reoccurring competition i.e. AFL (Bompa & Haff, 2009). Specific to AFL, matches are played on a weekly basis and the amount of days between games varies depending on the fixture design (Moreira et al., 2015). To best prepare players for their preceding match, training loads, more specifically, volume and intensity are manipulated during the week and session design is periodised around how many days break there is between matches i.e., match turnaround length.

There is a known difference between the load accumulated throughout training sessions when compared to matches given the difficulties in replicating match demands in training sessions (Corbett et al., 2017; Gabbett & Mulvey, 2008). These difficulties are reported in the literature and are prevalent given the dynamic nature of AFL (Appleby & Dawson, 2002), where training should be prescribed based on both physical and technical capacities (Corbett et al., 2017). Within these capacities, there are multiple constraints that can affect both the physical and tactical capacities relating to the individual (anthropometric variables, physiological capability), environment (external pressure) and task (rules and requirements within the drills)(Corbett et al., 2017; Magill, 2021). However, it is unknown whether the volume of distance and intensity accumulated during a match is influenced by the number of days break the players have between matches (between match turnaround length).

Between match turnaround length has been reported to influence match performance and the training volume within the training week regarding total volume (Colby et al., 2014; Drew & Finch, 2016; Mujika et al., 1995). It is known that training loads are manipulated based on fixtures which dictate the turnaround length between matches, however, this reduction in training load can be a combination of multiple factors such as; reduced training exposure, greater emphasis on recovery, lower intensity sessions or education sessions, however, this reduction is often underreported in the literature for the exact reasoning. Short turnaround lengths of <6-days and longer turnaround lengths of >7-12 days have reduced total training distances when compared to turnaround lengths greater than 12 days (Esmaeili et al., 2020; Ryan et al., 2017). Shorter turnaround lengths provide less opportunity for players to train (Ryan et al., 2017) given AF players require four days post-match to recover their neuromuscular and endocrine responses (Cormack et al., 2008). Despite this, there are no negative effects on high-speed running distances in matches when having a short or long turnaround length, suggesting these AF players are well conditioned in regard to their recovery, targeted at reducing fatigue (Esmaeili et al., 2020; Ryan et al., 2017). To ensure players are well conditioned and recovering, it is important to monitor the training being completed, specifically measuring variables such as position, displacement, velocity and acceleration (Aughey, 2011).

Acceleration is an important variable given an athlete's ability to accelerate and decelerate quickly impacts performance (Ellens et al., 2022) through an accumulation of high intensity workloads (Osgnach et al., 2010). Distance (m), speed ($m \cdot min^{-1}$) and acceleration ($m \cdot min^{-1} \cdot s^{-1}$) are the most commonly monitored variables given how influential these metrics are on athlete performance (Johnston et al., 2018; Sullivan et al., 2014). Emphasised through the results found from the previous studies in this thesis, where there were clear differences in acceleration between different competition levels (Chapter 5) and pre-season phases and training drill modalities (Chapter 6). Further supporting acceleration being a key component when quantifying running demands of team sports, and AF specifically through this research. Despite the importance of monitoring acceleration, there are issues with data being misinterpreted due to the type of tracking technology used (Delves et al., 2021; Varley et al., 2017), software used (Buchheit et al., 2014) and the data filtering process (Delves et al., 2021; Varley et al., 2017). Previous research has recommended quantifying the absolute average acceleration instead of using whole-match or session averages (Delaney et al., 2017; Gabbett et al., 2014), however, acceleration is often reported in the literature in terms of total acceleration efforts (Wisbey et al., 2010) or acceleration load (Thornton et al., 2022), which are not comparable to the acceleration measured in this study. The volume of acceleration, represented through impulse ($kN \cdot s^{-1}$) has only been investigated through one research study in women's AF (Thornton et al., 2020), however the quantitative findings cannot be compared to this cohort. There has been a plethora of research examining the intensity experience in team sports (for a review see Weaving et al.

(2022)), however investigating the distribution of volume is a new approach where there is a lack of research to provide comparable findings.

Understanding how speed and acceleration accumulate across the training week and across different between match turnaround lengths would aid practitioners in regard to their training prescription and design. Future training design can be manipulated seeking to replicate distances accumulated at maximal speed and accelerations identified through the cumulative distribution model, which provides an opportunity to replicate match demands in training. Additionally, providing further context as to whether the number of days between matches influences players the volume of speed and acceleration accumulated and the intensity at which the volume is accumulated at. To best position practitioners to understand this accumulation, it is recommended to work with larger amounts of data to eliminate the need for summating or averaging data and hence, risk losing context (Wilke, 2019). Aggregate methods such as a cumulative distribution as introduced through Chapter 5 & 6 of this thesis, can provide clear information around the distribution of speed and acceleration across the training week and compare amongst different turnaround lengths, which is yet to be examined, specifically in AFL. Therefore, the aim of this study was to examine the cumulative distribution of volume during different between match turnaround lengths for the 2022 AFL premiership home and away season. Secondly, to also identify what stage of the training week accumulates the greatest volume (training or matches) and whether this varies between different turnaround lengths. Answers to these questions could assist with providing greater context to the existing knowledge by acknowledging the changes reflected through acceleration which is an underreported area and also provide a visual representation of how the volume is accumulating as opposed to single figures stating maximal achieved for various metrics.

7.2 Methods

7.2.1 Participants

Forty-three professional AFL league players (age; 24 ± 4 yr, mass; 84 ± 10 kg and stature; 189 ± 8 cm) from the same club were recruited for this study. Data were collected over the 2022 AFL competitive season period running from March 2022 through to September

2022. The typical training week for players consisted of 1-3 field sessions, 1-3 resistance sessions and 1-2 additional on legs sessions consisting of either reduced volume, rehab, additional conditioning, skills training depending on the individual requirements of players. Players were classified by playing position as follows: forwards (n = 13), midfielders (n = 14), backs (n = 16). The mean (± SD) number of observations per athlete was 48 ± 12. Ethical approval for this research project was granted by the Victoria University Human Research Ethics Committee (HRE17-138).

7.2.2 Study Design

The study design implemented in this chapter follows that outlined in chapter 3.2.1 of this thesis where the specific data collected relevant to this study was that from main training sessions and matches. Of the matches, 2 were recorded using LPS due to playing at an enclosed stadium (Broadcaster Version 3.4.1).

The specific comparisons to meet the aims of this study where; quarters and competition level. When calculating total volume and impulse within each zone, this was split into each match quarter as well as competition level. Visual inspection of the logarithm of the cumulative volume and intensity for both distance and impulse showed a quadratic (non-linear curvilinear) relationship for quarter and game totals. To describe the distribution of distance and impulse across the intensity spectrum quadratic models were established for each player for each quarter and game. All files were categorised into different groups dependent on the number of days between the teams matches according to the 2022 AFL season fixture (between match turnaround length). The between match turnaround lengths included; less than seven days (<7), either seven or eight days (7-8) or more than eight days (>8). Between match turnaround length categories were decided based upon the number of observations recorded where the three categorise used provided an even spread of data across each. The total volume of distance and impulse in each zone across each between match turnaround length for main training sessions and matches were calculated. The cumulative volume was then established relative to intensity for each variable.

Visual inspection of the logarithm of the cumulative volume and intensity for both distance and impulse showed a quadratic (non-linear curvilinear) relationship for each between match turnaround length total. To describe the distribution of distance and impulse across the intensity spectrum quadratic models were established for each athlete for between match turnaround length.

7.2.3 Statistical Analysis

The statistical analysis used in this chapter is outlined in chapter 3.2.2 of this thesis, where the specifics of this chapter will be outlined. Linear mixed models were used to compare the quadratic coefficients from each model across the different between match turnaround lengths (<7, 7-8 and >8) for matches and main training sessions. Specifically, between match turnaround length and training drill modality was entered as the predictor (fixed effect).

7.3 Results

Table 7-1 presents the coefficients for the speed distance and impulse acceleration models for the between match turnaround lengths (<7, 7-8 and >8) and modalities (training and matches). Figure 7-1 depicts the distance accumulated in the quadratic equations for between match turnaround lengths and modalities for the speed coefficients comparing absolute distance (A) and relative distance (B). Figure 7-2 demonstrates the comparisons between match turnaround lengths and modalities for the distance speed model coefficients (*a*, *b* and *c*). When comparing turnaround length data, speed coefficient *c* for training sessions was substantially higher for >8 day turnarounds compared to 7-8 days (ES = -0.32; ±90% CL = 0.17). A point to note regarding Figure 7-2, is the confidence limits for coefficient *b* for the comparison within training sessions from <7 day and >8 day between match turnaround length is wide given there is a high degree of uncertainty with the data recorded for this specific coefficient within this comparison.

Figure 7-3 displays the distance accumulated in the quadratic equations between match turnaround lengths and modalities for the acceleration coefficients comparing absolute distance (A) and relative distance (B). Figure 7-4 demonstrates the comparisons between match turnaround lengths and modalities for the impulse acceleration model coefficients (*a*, *b* and *c*). No comparisons for the impulse acceleration model were significant.

Table 7–1 Coefficients (*a*, *b* and *c*) for speed distance and impulse acceleration model for the different between match turnaround lengths (<7-days, 7-8-days and >8-days) for the two different modalities (training and matches).

	Speed Distance Model			**Impulse Acceleration Model**		
	a	*b*	*c*	*a*	*b*	*c*
Training: <7-days	-0.03 (0.01)	9.0 (1.5)	214 (80)	-0.50 (0.20)	37.7 (7.8)	539 (101)
Training: 7-8-days	-0.03 (0.01)	9.0 (1.4)	230 (84)	-0.50 (0.16)	37.1 (7.6)	559 (92)
Training: >8-days	-0.03 (0.01)	9.1 (1.6)	203 (84)	-0.49 (0.31)	35.8 (10.1)	557 (103)
Match: <7-days	-0.02 (0.01)	6.7 (1.4)	286 (74)	-0.31 (0.09)	26.6 (5.1)	691 (68)
Match: 7-8-days	-0.02 (0.00)	6.7 (1.3)	286 (69)	-0.30 (0.09)	26.2 (5.3)	689 (81)
Match: >8-days	-0.02 (0.00)	6.8 (1.2)	293 (66)	-0.32 (0.09)	27.1 (5.2)	693 (71)

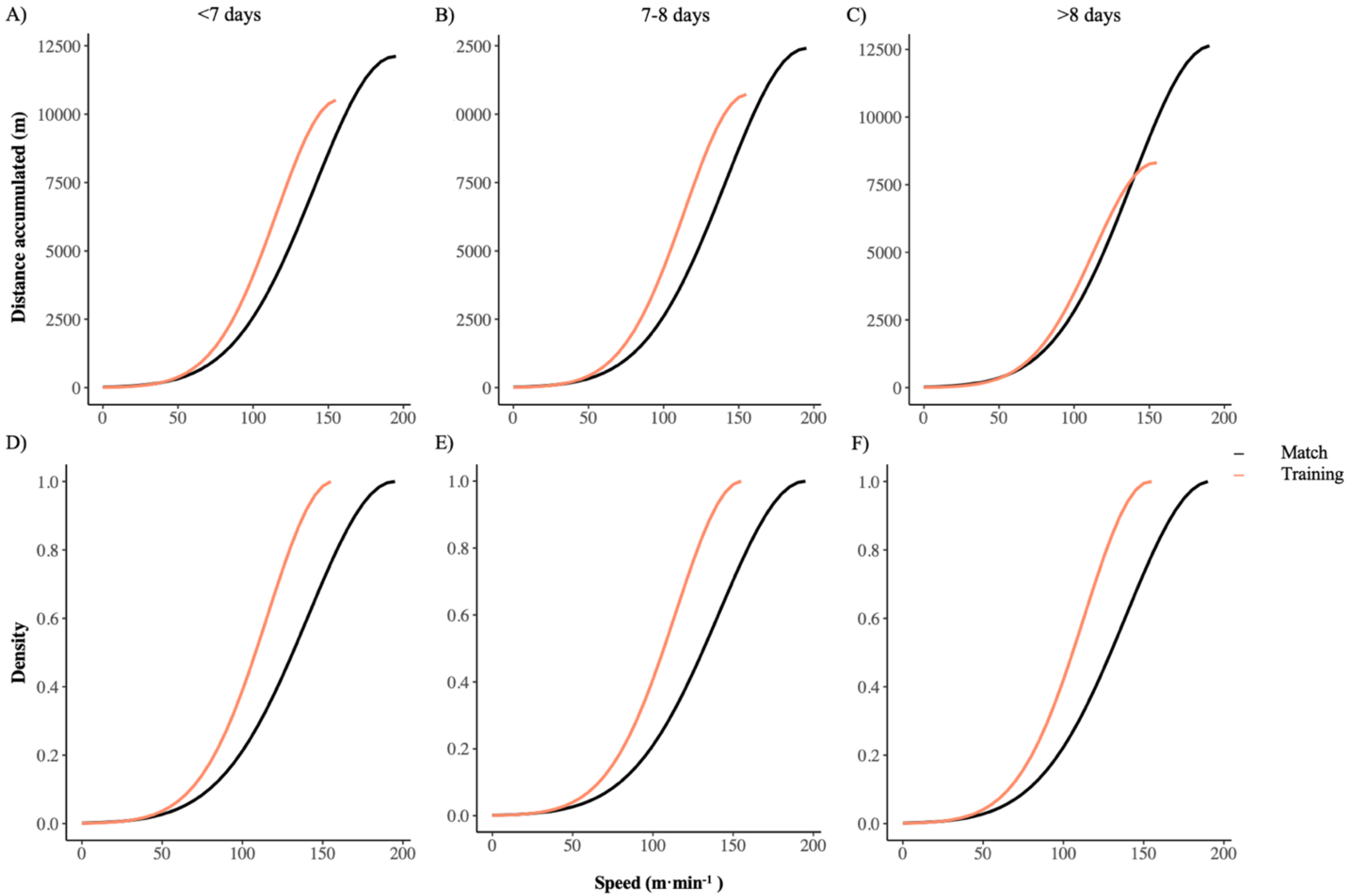

Figure 7–1 The cumulative distribution of distance in relation to speed expressed as a quadratic equation for all between match turnaround lengths (<7-days, 7-8-days and >8-days) and modalities (training and matches) displaying absolute distance (top panels) and relative distance (bottom panels) in AF.

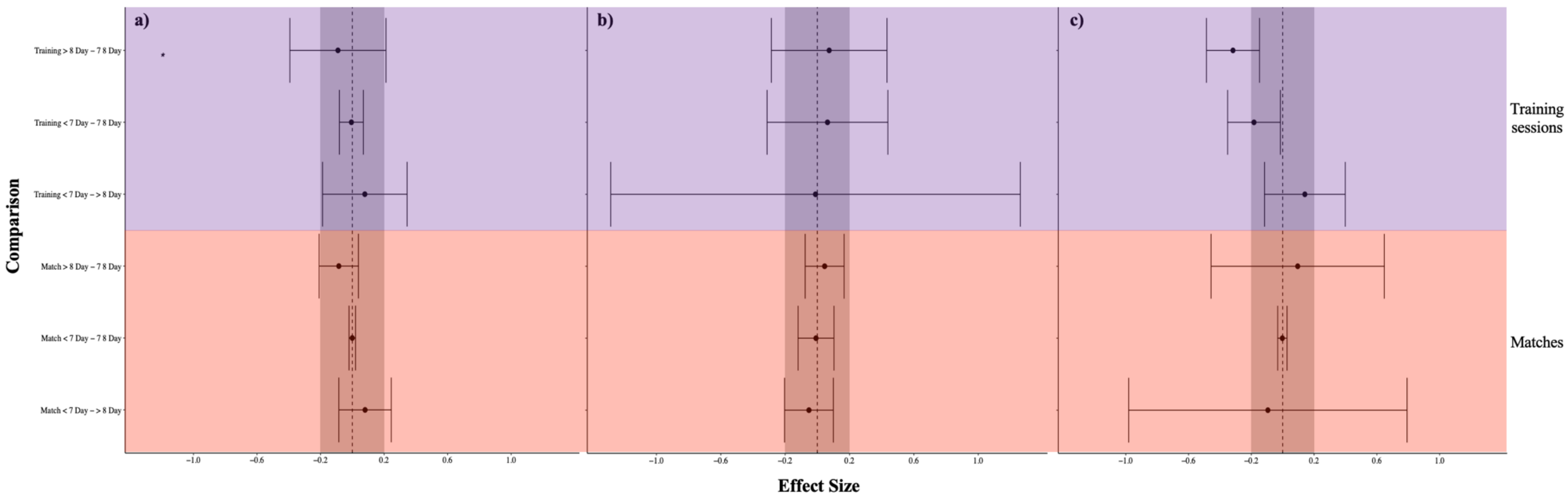

Figure 7–2 Comparison of speed quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between match turnaround lengths (<7-days, 7-8-days and >8-days) and modalities (training and matches). Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across the shaded area (– 0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES).

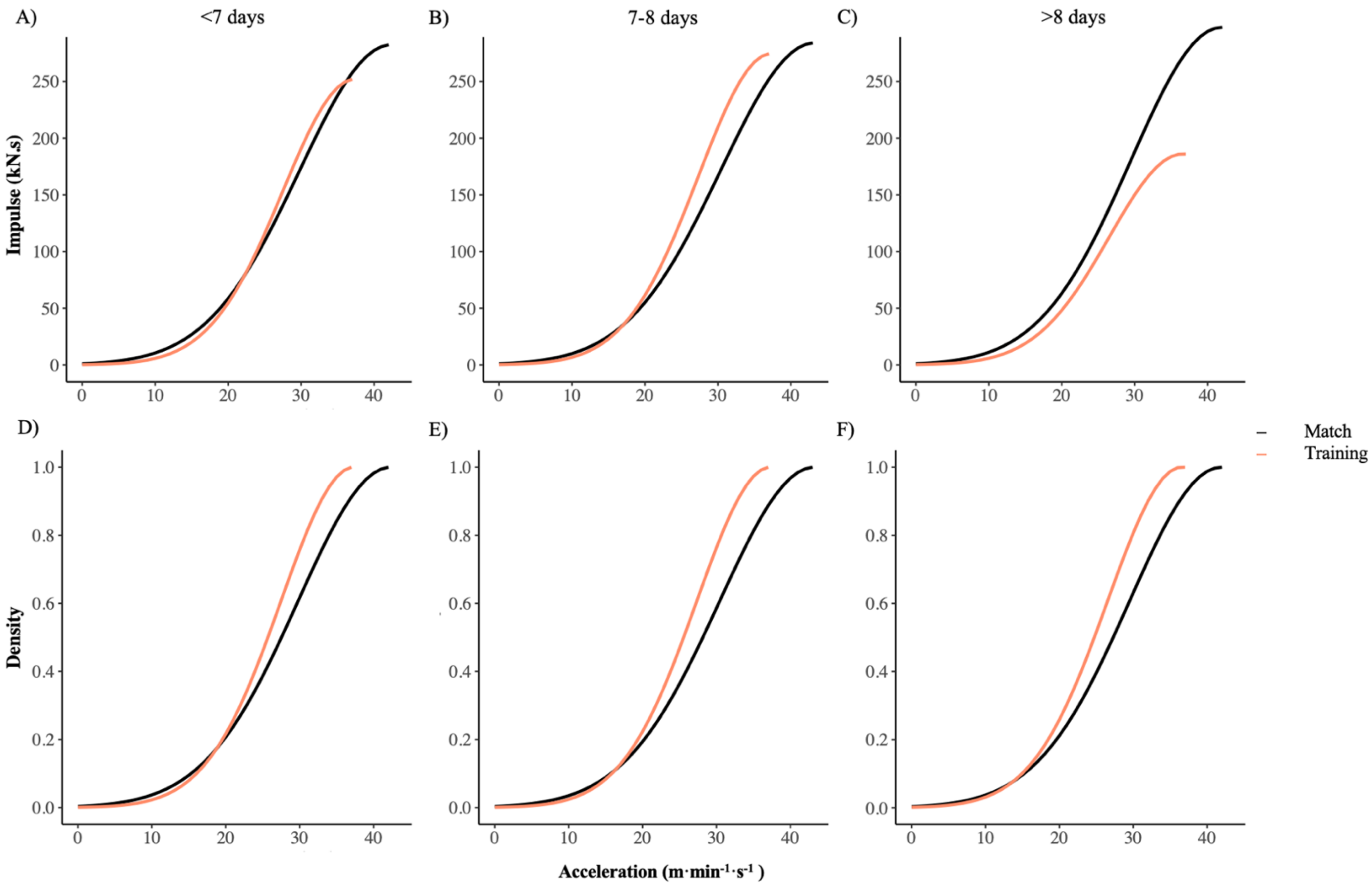

Figure 7–3 The cumulative distribution of distance in relation to acceleration expressed as a quadratic equation for all between match turnaround lengths (<7-days, 7-8-days and >8-days) and modalities (training and matches) displaying absolute impulse (top panels) and relative impulse (bottom panels) in AF.

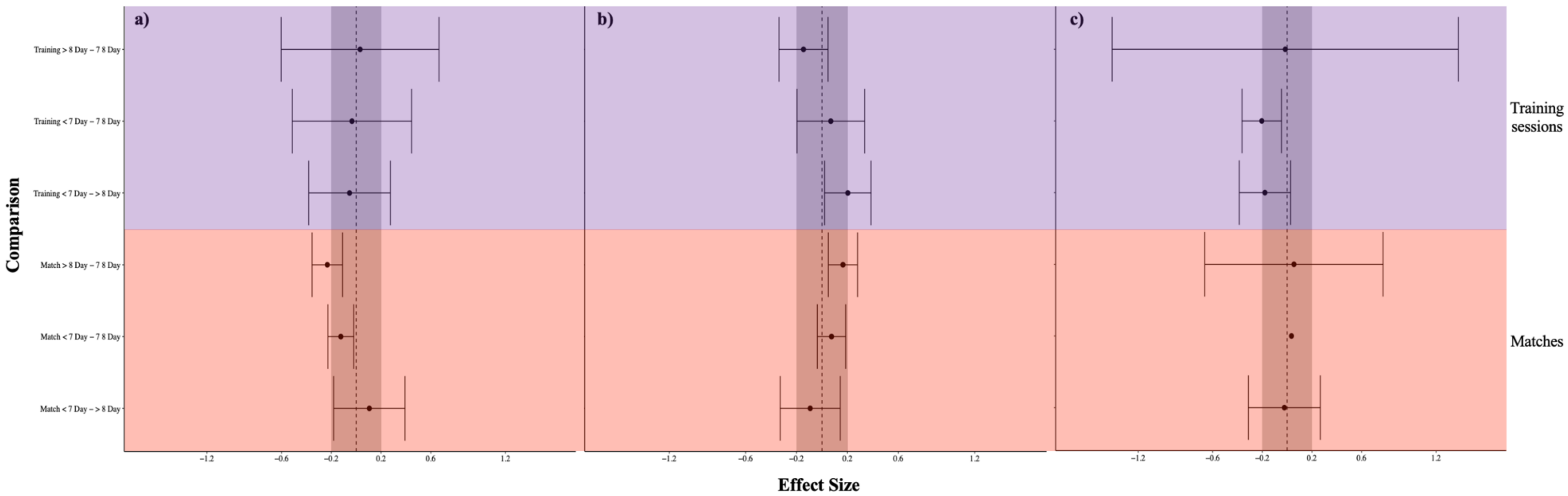

Figure 7–4 Comparison of acceleration quadratic coefficients *a* (Figure a), *b* (Figure b) and *c* (Figure c) between match turnaround lengths (<7-days, 7-8-days and >8-days) and modalities (training and matches). Differences are expressed using effect sizes and 90% confidence intervals and were deemed as unclear if the confidence limits spanned entirely across the shaded area (– 0.20 to 0.20).

* Effect size greater than 75% of the smallest worthwhile change (0.20 ES).

7.4 Discussion

The purpose of this study was to investigate the accumulation of volume across the intensity spectrum for speed and acceleration across the different match turnaround lengths during an entire AF season. A secondary aim was to confirm the greatest volume is accumulated in matches and provide further context around the changes between intensity across the various between match turnaround lengths. The cumulative volume distribution analysis used in this study showed a clear difference between the volume accumulated in matches and training sessions. Matches are expected to have the greatest volume during a training week (Ritchie et al., 2016), however, comparing the volume during matches across different between match turnaround lengths is a new investigation. These aims served to build upon existing research and fill the missing gaps regarding acceleration and also provide a visual representation of how volume is accumulating to provide greater insight.

Matches accumulated the greatest weekly distance being, 12.6 km for >8-day, 12.4 km for 7-8-day and 12.1 km for <7-day between match turnaround lengths and achieved one-minute maximal mean speeds of 190 $m \cdot min^{-1}$ for >8-day and 195 $m \cdot min^{-1}$ for both 7-8-day and <7-day turnaround lengths. Where training sessions only accumulated weekly distances of 8.3 km for >8-day, 10.7 km for 7-8-day and 10.5 km for <7-day between match turnaround lengths and achieved one-minute maximal speeds of 155 $m \cdot min^{-1}$ for all between match turnaround lengths. There is a clear difference in the one-minute maximal mean speed achieved through matches when compared to training sessions, where matches regardless of the between match turnaround length will accumulate higher one-minute mean speeds. Given the known challenges of replicating match intensity and volume in training (Corbett et al., 2017; Gabbett & Mulvey, 2008), it has been shown that matches achieve higher maximum speeds compared to training (Ritchie et al., 2016). Greater than eight-day between match turnaround lengths have the lowest one-minute maximal mean speed and lowest distance accumulated suggesting this is the least intense between match turnaround length when considering overall training load. There was one substantial difference in the quadratic coefficients (*a, b* and *c*). Specifically, the higher *c* coefficient for >8-day between match turnaround length compared to 7-8-day turnaround, reflecting more distance was accumulated at lower speeds for the >8-day turnaround compared to the 7-8-day between match turnaround length which supports being the least intense between match turnaround length. This suggests, that in a longer between match turnaround week there is a greater focus on recovery compared to shorter between match turnaround lengths.

Training prescription needs to maintain performance whilst also reduce the risk of injury (Colby et al., 2014; Drew & Finch, 2016; Mujika et al., 1995), where recovery sessions are emphasised between training sessions to aid in preparing players for their next competition (Bahnert et al., 2013; Barnett, 2006). When comparing the volume accumulated in training sessions, there was a substantial difference from >8-day turnaround (8.3 km) to 7-8-day between match turnaround length (10.7 km). The notable difference between these between match turnaround lengths is the number of days between matches which has a direct influence on the amount of training sessions prescribed, therefore effecting the periodisation of training. Suggesting there is a greater emphasis on recovery in the weeks with a longer between match turnaround length, given the reduction in training volume compared to a shorter between match turnaround length. Previous research in collision sports has stated during shorter between match turnaround lengths, there are fewer training sessions when compared to longer between match turnaround lengths, therefore training volume needs to be maximised in these sessions (Gabbett & Domrow, 2007; Gabbett, 2004). Given this research you would expect >8-day between match turnaround lengths to have a higher training volume as there are likely more sessions given there is more days in which the players can train between their matches. Contrary to this, for this respective season in AFL, the between match turnaround lengths >8-day are all bar one due to a bye, where the remaining one was from the Easter period in which players are given a 4-day break to recover post-match. Based on this, there was less opportunity to train therefore accounting for this reduction in volume for >8-day between match turnaround lengths. Therefore, the training week with a between match turnaround length >8-days may not be consistent with other between match turnaround lengths (Wing et al., 2021). Determining this reduction in speed and volume as unconfirmed whether it is a result of the type of training between match turnarounds of this length or due to external factors i.e., 4-day break, extra days off, more recovery sessions. These reductions in speed and volume in between match turnaround lengths >8-day are the opposite of what can be seen in the impulse acceleration model.

A key physical quality for AF performance is acceleration (Aughey, 2010; Johnston et al., 2015d), justifying the importance of understanding how acceleration is accumulated throughout the training week and where any differences arise to aid practitioners in preparing players for the demands of AF and taking these values into consideration when prescribing recovery. Across all between match turnaround lengths, >8-day turnaround accumulated the greatest volume of impulse being 298 kN·s, where 7–8-day between match turnaround length accumulated 284 kN·s and <7-day between match turnaround length accumulated 282 kN·s. Further analysing these between match turnaround lengths, >8-day and <7-day between match turnaround lengths accumulated impulse at the same acceleration of 42 $m \cdot min^{-1} \cdot s^{-1}$ where 7-8-day between match turnaround accumulated impulse at a slightly higher acceleration of 43 $m \cdot min^{-1} \cdot s^{-1}$. Similar to the findings from the speed distance model, matches regardless of between match turnaround length, always accumulated a greater volume of impulse and at higher accelerations compared to training sessions. All training sessions achieved the same one-minute maximal mean acceleration of 37 $m \cdot min^{-1} \cdot s^{-1}$ where the volume accumulated was greatest for >8-day between match turnaround length being 274 kN·s, followed by <7-day between match turnaround length (252 kN·s) and lastly 7–8-day between match turnaround lengths (186 kN·s). These difference between training and matches can further be seen in the rightward shift of the curve for matches in Figure 7-3 indicating volume is accumulated at a higher intensity. There is limited comparison available with regards to how acceleration was analysed within this study as previous research reports acceleration as a value of efforts (Wisbey et al., 2010) or acceleration load (Thornton et al., 2020).

Overall, the findings of this research indicate that there are differences in speed and acceleration between turnaround lengths when comparing between modalities. This study used a novel approach to quantify the volume and intensity of running that occurs throughout an entire AF competitive phase, that has important practical applications for those monitoring training for AF players. This information can assist practitioners in training design when prescribing the season given, this research has shown as long as training is periodically manipulated according to the days break between matches, there is no detrimental effect on maximal speed and acceleration the players are able to achieve in matches. Through the use of a cumulative distribution, whole training and match files were visually displayed as opposed to summation value in pre-determined thresholds.

This analysis demonstrated that both speed and acceleration are important when differentiating between match turnarounds lengths in regard to the modality. Where greater speed and distance is accumulated in matches compared to training sessions irrespective of between match turnaround length. Further, >8-day between match turnaround lengths accumulate greater impulse at a higher intensity compared to 7-8-day and <7-day between match turnaround lengths. These findings confirm that matches are the most intense activity and accumulate the most distance within a training week in AF and that with appropriate periodisation, speed and acceleration in matches are not affected based on the between match turnaround length.

The underlying limitation of this study revolves around the categorisation of different between match turnaround lengths. The decisions made in this study were based on the data set available and appropriate sample sizes to have sufficient observations in each category. Future research should endeavour to use a larger data set in turn providing a larger number of observations so the categories for different match turnaround lengths can be justified with greater strength and may highlight greater relationships based on larger sample sizes for each match turnaround length.

CHAPTER 8. SUMMARY AND CONCLUSIONS

8.1 Main Findings

Training periodisation is a known important concept to expose players to structured and monitored training loads to provide the opportunity for training adaptations designed to improve performance (Bompa & Haff, 2009). Training can be manipulated through volume and intensity which is reflected through variables such as, total distance, high speed distance, maximal speed and acceleration (Bompa & Haff, 2009; deCunanan et al., 2018; Mujika et al., 2018). Selecting the most applicable monitoring tools to track these variables is of upmost importance for practitioners and is not a simple answer as there are countless tools available. The ability to predict match performance based from training data would be beneficial to practitioners as this could assist with team selection and match decisions. However, no such monitoring tool has been developed and validated to consistently infer match performance within the scope of this research. There are reported difficulties with replicating match demands in training due to the dynamic nature of AF (Appleby & Dawson, 2002), suggesting if new approaches that have not previously been recorded are considered, targeted at replicating match demands, this may assist in being able to predict match performance. Speed and acceleration are known important variables within AF (Aughey, 2010; Johnston et al., 2015b) where acceleration is under reported in the literature due to a range of different metrics being used to quantify this running activity, thus making comparisons difficult. This suggests that more research is required investigating acceleration during training and matches in AF to fill the gap in this research area.

To address the aims of this thesis, four studies were conducted. **Study 1** investigated the use of common monitoring tools in their correlation to performance identified through Champion Data© ratings points. In **study 2**, a novel approach was used to analyse the GNSS data recorded from matches to provide further context around how distance is being accumulated across matches and between different competition levels. **Study 3** expanded on **study 2,** in which the same analysis was used but applied to different conditions, being the comparison between different pre-season phases and training drill modalities. This understanding can further assist practitioners in their training prescription and design by understanding how distance is accumulated across the speed spectrum. Lastly, **study 4** quantified the difference between match turnaround lengths and training drill modalities. This study provided context regarding if there are any effects on speed and acceleration profiles across different match turnaround lengths. The main findings are summarised as;

- **Study 1** found that none of the current training monitoring tools implemented by the club included in the study showed any substantial relationship with match performance, therefore, predicting players' performance using wellness questionnaires or current GNSS monitoring variables have limited practical use.
- **Study 2** quantified the distribution of speed and acceleration between quarters and competition level in AF. It was demonstrated that AFL players accumulate distance and impulse at higher intensity then those in VFL.
- **Study 2** found within AF matches, quarter one accumulates greater distance at higher intensity compared to that of quarter four, suggesting fatigue is a likely contributor across match duration.
- **Study 3** showed that conditioning drills accumulate impulse at the highest intensity. When investigating skill based training drills, game plan drills accumulated impulse at the highest intensity and therefore are the most intense skill based drill.
- **Study 3** determined that the post-Christmas pre-season phase accumulates the greatest volume of speed and acceleration.
- **Study 4** identified match turnaround length doesn't appear to substantially affect the speed and acceleration distribution in training, however it was found that matches regardless of turnaround length always accumulate the greatest distance at a higher intensity.

All quantified findings reported from each study may not have direct replicability to other AF clubs and competition levels, however, a similar pattern would be expected for all comparisons based on the known information around typically training structure within AF. Given the nature of the AFL competition exposes all clubs at the elite level to a rotating fixture where each club experiences various between match turnaround lengths, typical training structure follows two or three main training sessions (match turnaround length dependent), three pre-season phases and various skills and conditioning based training drills. The main limiting factor for the ability of these results to be compared would be the way training drill modalities were determined in this study, as this was specific to this particular AF club, however, specific work rate thresholds were identified for future research to be adapted to, providing scope for direct comparisons to be made.

8.2 Summary

Speed and acceleration are important variables within AF (Aughey, 2010; Johnston et al., 2015b) and the distribution of speed and acceleration does vary across different conditions within training and matches. The distribution of speed across all comparisons from this thesis can be seen in Figure 8-1 and the distribution of acceleration can be seen in Figure 8-2.

Acceleration is a key variable in identifying differences between competition levels, training drill modalities and between match turnaround length. It is clear that matches accumulate the greatest distance within a training week in AF (**Study 4**), where >8 day between match turnaround lengths are the most intense matches (**Study 4**) and quarter one accumulates the greatest volume of both speed and acceleration at the highest intensity (**Study 2**). When investigating training sessions, the post-Christmas pre-season phase accumulated the largest amount of volume, maintaining a high intensity (**Study 3**), where conditioning drills accumulate the greatest impulse and game plan drills are the most intense (**Study 3**).

8.3 Limitations

Throughout this thesis there were factors identified that could be at fault for the nil findings or areas that could be expanded on to further develop the knowledge sought after through the various studies where the limitations are described below.

1. In **Study 1** Champion Data© rating points and coaches subjective ratings had no statistically significant correlation on each other identifying that they are quantifying different aspects if the game and therefore preference cannot be given to one over the other in regard to measuring performance. Champion Data© rating points measure players performance objectively through quantifiable actions whereby coaches measure players performance subjectively, often thought to be influenced by quantifiable actions. However, there is room for bias and this was not investigated through this research.

2. **Study 1** found no meaningful relationship between GNSS, wellness metrics, Champion Data© rating points, or coaches subjective ratings. This suggests that these variables cannot be used to predict performance in a practical setting. It could be suggested that more insight could be gleaned by using a metric better aligned with performance, such as acceleration which was not analysed in this study. Wellness monitoring can be a heavily biased monitoring tool when using an adapted AROM scale that has not been validated which is common practice and was employed at this particular club whereby this data was collected. This can lead to players becoming accustomed to answering with a particular answer without providing much thought to the response for various cognitive and situational factors discussed previously in section 2.5.3.2. It therefore poses the potential that the results are not a true representation of how the players are feeling. This is hard to eliminate and perhaps emphasises that the particular wellness questionnaire utilised in this club is not an appropriate tool to assess performance. Regardless, wellness monitoring can still be used to quickly assess the athlete and provides a conversational piece to gain insight into players subjective states. This study identified that future research should consider objective tools that have higher correlation with performance such as acceleration, prompting the direction for the proceeding studies completed or utilising a validated AROM to provide training effect status of players.
3. In **Study 2**, matches were compared between different competition levels being AFL and VFL. It was concluded that the overall volume accumulated in AFL is higher than that in VFL. The difference between competition levels can be observed at 150 $m \cdot min^{-1}$ where AFL accumulates more distance at and greater than this speed in comparison to VFL. In comparison VFL demonstrates a greater accumulation of distance at lower speeds. When examining acceleration, the rightwards shift in the distribution AFL indicates a higher maximal acceleration is achieved and more impulse is accumulated at higher intensities. In contrast, VFL displayed a greater overall total volume of impulse indicating a higher volume of acceleration and decelerations at lower intensities.

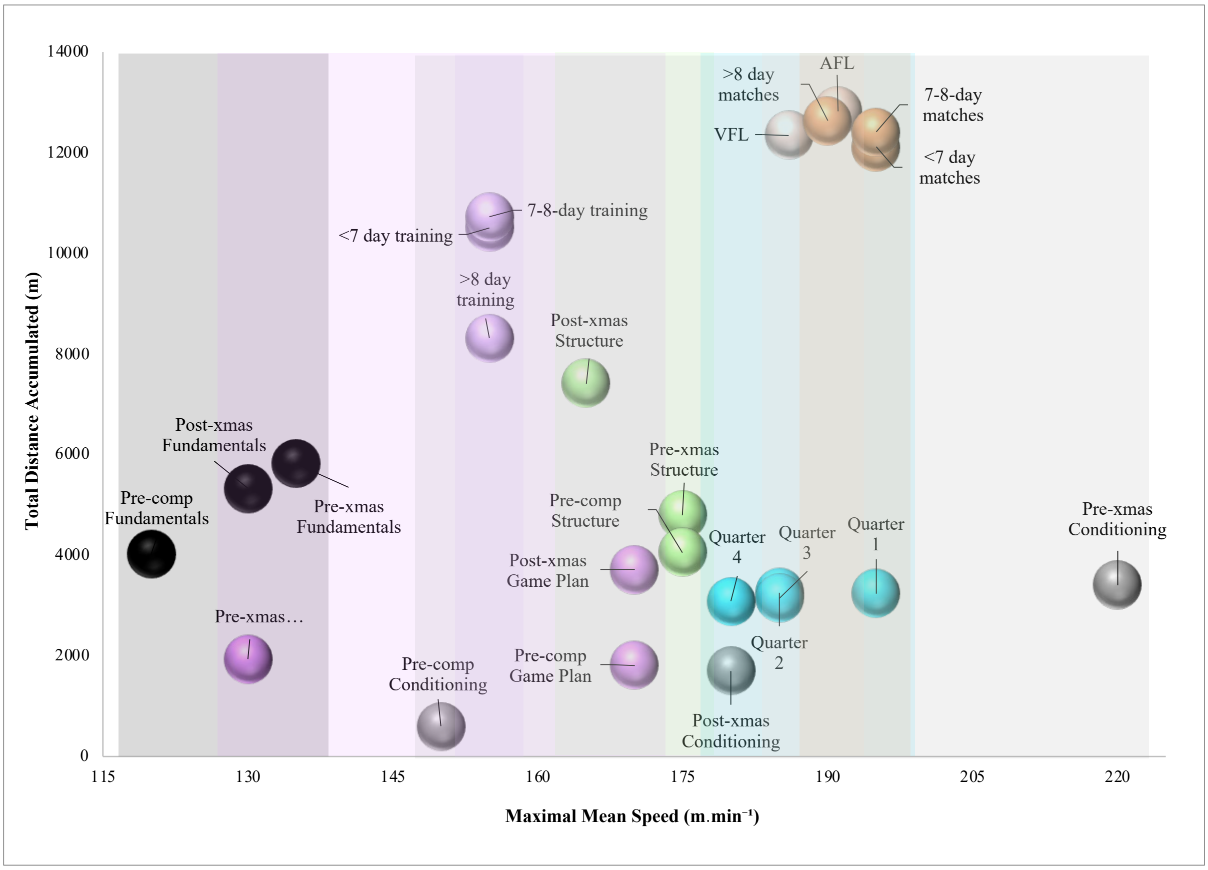

Figure 8–1 Volume of distance accumulated at varying speed for each comparison investigated throughout the thesis from studies 2-4. The *x* axis displays the maximal one minute acceleration achieved by each comparison made throughout all of the data observations reported in studies 2-4 and the total impulse accumulated at that maximal acceleration on the *y* axis. Training comparisons can be categorised as; Pre-xmas Fundamentals, Post-xmas Fundamentals, Pre-comp Fundamentals, Pre-xmas Structure, Post-xmas Structure, Pre-comp Structure, Pre-xmas Game Plan, Post-xmas Game Plan, Pre-comp Game Plan, Pre-xmas Conditioning, Post-xmas Conditioning, Pre-comp Conditioning, <7-day training, 7-8-day training and >8-day training. Match comparisons encompass; Quarter 1, Quarter 2, Quarter 3, Quarter 4, VFL, AFL, <7-day matches, 7-8-day matches and >8-day matches. Each training comparison is reported as a maximal value accrued in a training session and match comparisons within a singular match.

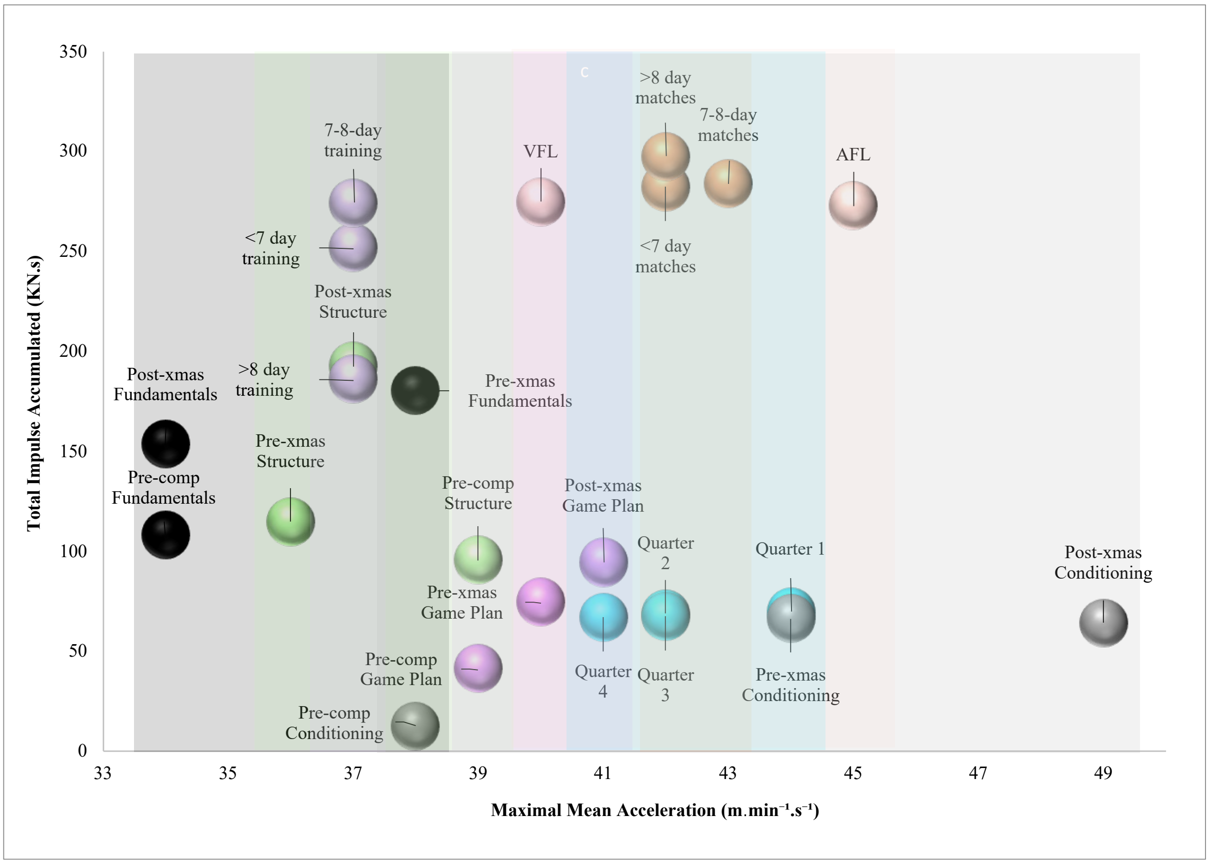

Figure 8–2 Volume of impulse accumulated at varying acceleration for each comparison investigated throughout the thesis from studies 2-4. The *x* axis displays the maximal one minute acceleration achieved by each comparison made throughout all of the data observations reported in studies 2-4 and the total impulse accumulated at that maximal acceleration on the *y* axis. Training comparisons can be categorised as; Pre-xmas Fundamentals, Post-xmas Fundamentals, Pre-comp Fundamentals, Pre-xmas Structure, Post-xmas Structure, Pre-comp Structure, Pre-xmas Game Plan, Post-xmas Game Plan, Pre-comp Game Plan, Pre-xmas Conditioning, Post-xmas Conditioning, Pre-comp Conditioning, <7-day training, 7-8-day training and >8-day training. Match comparisons encompass; Quarter 1, Quarter 2, Quarter 3, Quarter 4, VFL, AFL, <7-day matches, 7-8-day matches and >8-day matches. Each training comparison is reported as a maximal value accrued in a training session and match comparisons within a singular match.

4. In **Study 3**, pre-season phases and training drill modalities were split into arbitrary categories determined by the high performance team within the AFL club. The pre-season phases appear to be similar to previous reports published, however, this was the first investigation quantifying the volume and intensity of different training drill modalities. The training drills were categorised into four groups based on the style of the training and the expected work rate experience in each drill. For skill based training drills there were three categories; fundamentals, structure and game plan, with the final non-skill based category being conditioning. Conditioning is comparable to previous research as this is heavily reported, however, the categorisation of skills based training in comparison to training load is a novel approach and can be a limitation for future studies to compare to if they do not classify their drills in the same way. The classification of training drill modalities in this study is highly specific to the AFL club the research was produced from and for comparable results to other studies, their analysis would need to categorise their drills in the same work rate ranges.
5. **Study 4** compared the differences in volume accumulated across different between match day turnarounds. The limitation of this study would be the categorisation of different between match turnaround lengths. For this particular study the three categories were <7- day, 7-8-day and >8-day and was done this way based on the number of observations, to provide an equal spread of data. It could be argued for future research, to use a larger data sample size, either from multiple seasons or multiple clubs. Allowing for more observations to be collected allowing each turn around length to be analysed individually i.e., 6-day, 7-day, 8-day, etc. This has the potential to build upon the findings here and specify why turn around lengths exactly have a greater intensity and distance covered and the reasoning behind this.

8.4 Conclusion and recommendations

In conclusion this thesis provides new information about the distribution of speed and acceleration across the intensity spectrum which has not previously been reported in AF and also builds on pre-existing knowledge around training monitoring and training periodisation.

- Wellness monitoring is a practical tool for driving conversation between players and staff however, invalidated or adapted AROMs should not be implemented as a means of trying to predict performance without going through means of validation to ensure they are assessing and collecting practically meaningful data as identified through the conceptual framework discussed in section 2.5.3.2.
- Total distance and other speed related metrics (high-speed running, work rate, maximum velocity etc.) have no correlation with match performance from a subjective or objective perspective. **Study 1** identified performance is a difficult concept to quantify and may be best investigated through a metric that is correlated with ball involvement such as acceleration.
- In **study 2** when acceleration was analysed, the cumulative distribution model used displayed the significant differences in acceleration between competition levels where it was shown AFL accumulates greater impulse at a higher intensity than VFL. This study was also able to identify quarter one regardless of competition level, accumulated the greatest distance and impulse at a higher intensity, whereby both metrics decline through to quarter four.
- Acceleration was further investigated, more specifically throughout training in pre-season where the post-Christmas phase was determined to accumulate the greatest amount of volume at a high intensity, more specifically game plan drills are executed at the highest intensity and conditioning drills accumulate the greatest amount of impulse within a pre-season in AF.
- Following on from pre-season, in season when investigating where the greatest volume is accumulated within the week, matches irrespective of the between match turnaround length always accumulate greater impulse and distance. Further analysing matches between the different match turnaround lengths, matches of >8-day between match turnaround lengths accumulate the greatest amount of impulse at the highest intensity.

To improve future research, studies should attempt to further quantify more specific comparisons across larger data sets to establish clear thresholds between the comparisons made throughout these studies i.e., competition level, match quarters, pre-season phases, training drills modalities and match turnaround length. Acceleration should be continually investigated given the known importance of this variable and how it appears to be the most influence/manipulated between athletes of varying comparisons. The research should also continue to employ the cumulative distribution technique as it provides a useful tool for practitioners given its visual capacity and the use of coefficients to interpret meaningful differences. With greater research replicated in the field it will close the gap on what volume and intensity is accumulated at varying competition levels and across different teams within the same competition levels which provide greater confirmation which can practically assist in training prescription and design.

REFERENCES

Ade, J. D., Harley, J. A., & Bradley, P. S. (2014). Physiological response, time-motion characteristics, and reproducibility of various speed-endurance drills in elite youth soccer players: small-sided games versus generic running. *International Journal of Sports Physiology and Performance, 9*(3), 471-479. https://doi.org/10.1123/ijspp.2013-0390

Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *ACM SIGMOD Record, 22*(2), 207-216. https://doi.org/10.1145/170036.170072

Akenhead, R., Harley, J. A., & Tweddle, S. P. (2016). Examining the external training load of an english premier league football team with special reference to acceleration. *Journal of Strength and Conditioning Research, 30*(9), 2424-2432. https://doi.org/10.1519/JSC.0000000000001343

Algroy, E. A., Hetlelid, K. J., Seiler, S., & Pedersen, J. I. S. (2011). Quantifying training intensity distribution in a group of Norwegian professional soccer players. *International Journal of Sports Physiology and Performance, 6*(1), 70-81.

Anagnostopoulos, T., Anagnostopoulos, C. B., Hadjiefthymiades, S., Kyriakakos, M., & Kalousis, A. (2007). Path prediction through data mining.

Appleby, B., & Dawson, B. (2002). Video analysis of selected game activities in Australian rules football. *Journal of Science and Medicine in Sport, 5*(2), 129-142.

Aubert, A. E., Seps, B., & Beckers, F. (2003). Heart rate variability in athletes. *Sports Medicine, 33*(12), 889-919.

Aughey, R. (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

Aughey, R. (2011). Applications of GPS technologies to field sports. *International Journal of Sports Physiology and Performance, 6*(3), 295-310.

Australian Academy of Science. (2022). *Getting ahead of the game: Athlete data in professional sport*.

Bahnert, A., Norton, K., & Lock, P. (2013). Association between post-game recovery protocols, physical and perceived recovery, and performance in elite Australian Football League players. *Journal of Science and Medicine in Sport, 16*(2), 151-156.

Banister, E. W., MacDougall, J. D., & Wenger, H. A. (1991). Modeling elite athletic performance. In *Physiological testing of the high-performance athlete* (pp. 403-425). Human Kinetics Books.

Barnett, A. (2006). Using recovery modalities between training sessions in elite athletes: Does it help? *Sports Medicine, 36*(9), 781-796. https://doi.org/10.2165/00007256-200636090-00005

Barris, S., Davids, K., & Farrow, D. (2013). Representative learning design in springboard diving: Is dry-land training representative of a pool dive? *European Journal Of Sport Science, 13*(6), 638-645.

Bartlett, J. D., O'Connor, F., Pitchford, N., Torres-Ronda, L., & Robertson, S. J. (2017). Relationships between internal and external training load in team-sport athletes: Evidence for an individualized approach. *International Journal of Sports Physiology and Performance, 12*(2), 230-234.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*(1), 1.

Beedie, C. J., Terry, P. C., & Lane, A. M. (2005). Distinctions between emotion and mood. *Cognition & Emotion, 19*(6), 847-878. https://doi.org/10.1080/02699930541000057

Bellenger, C. R., Fuller, J. T., Nelson, M. J., Hartland, M., Buckley, J. D., & Debenedictis, T. A. (2015). Predicting maximal aerobic speed through set distance time-trials. *European Journal Of Applied Physiology, 115*(12), 2593-2598.

Berkhin, P. (2006). A survey of clustering data mining techniques. In J. Kogan, C. K. Nicholas, & M. Teboulle (Eds.), *Grouping multidimensional data : recent advances in clustering*. Springer, Berlin, Heidelberg. https://doi.org/https://doi.org/10.1007/3-540-28349-8_2

Bilsborough, J. C., Greenway, K. G., Opar, D. A., Livingstone, S. G., Cordy, J. T., Bird, S. R., & Coutts, A. J. (2015). Comparison of anthropometry, upper-body strength, and lower-body power characteristics in different levels of Australian football players. *Journal of Strength & Conditioning Research, 29*(3), 826-834. https://doi.org/10.1519/jsc.0000000000000682

Birch, K., MacLaren, D., & George, K. (2005). *Sport and exercise physiology*. BIOS Scientific Publishers.

Bompa, T. O., & Haff, G. (2009). *Periodization: Theory and methodology of training* (F. edition., Ed.). Champaign, IL. : Human Kinetics.

Borg, G. (1990). Psychophysical scaling with applications in physical work and the perception of exertion. *Scandinavian Journal of Work, Environment and Health*, 55.

Borg, G. A. (1982). Psychophysical bases of perceived exertion. *Med Sci Sports Exerc, 14*(5), 377-381.

Borresen, J., & Lambert, M. I. (2009). The quantification of training load, the training response and the effect on performance. *Sports Medicine, 39*(9), 779-795.

Bouchard, C. (1983). *Human adaptability may have a genetic basis.* (F. Landry ed.). Ottawa: Canadian Public Health Association.

Bouchard, C., Gagnon, J., Pérusse, L., An, P., Rice, T., Rao, D. C., Skinner, J. S., Wilmore, J. H., & Leon, A. S. (1999). Familial aggregation of V̇O(2max) response to exercise training: Results from the HERITAGE family study. *Journal of Applied Physiology, 87*(3), 1003-1008.

Bouchard, C., & Rankinen, T. (2001). Individual differences in response to regular physical activity. *Med Sci Sports Exerc, 33*(6), 446-451.

Bourdon, P. C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M. C., Gabbett, T. J., Coutts, A. J., Burgess, D. J., Gregson, W., & Cable, N. T. (2017). Monitoring athlete training loads: Consensus statement. *International Journal of Sports Physiology and Performance, 12*, 161-170.

Boyd, L. J., Ball, K., & Aughey, R. J. (2011, Sep). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *International Journal of Sports Physiology and Performance, 6*(3), 311-321. https://doi.org/10.1123/ijspp.6.3.311

Boyd, L. J., Ball, K., & Aughey, R. J. (2013). Quantifying external load in Australian Football matches and training using accelerometers. *International Journal of Sports Physiology and Performance, 8*(1), 44-51.

Bredt, S., Chagas, M. H., Peixoto, G. H., Menzel, H. J., & de Andrade, A. G. P. (2020). Understanding Player Load: Meanings and limitations. *Journal of Human Kinetics, 71*, 5-9. https://doi.org/10.2478/hukin-2019-0072

Brener, N. D., Billy, J. O., & Grady, W. R. (2003). Assessment of factors affecting the validity of self-reported health-risk behavior among adolescents: evidence from the scientific literature. *The Journal of Adolescent Health 33*(6), 436-457.

Brewer, C., Dawson, B., Heasman, J., Stewart, G., & Cormack, S. (2010). Movement pattern comparisons in elite (AFL) and sub-elite (WAFL) Australian Football games using GPS. *Journal of Science and Medicine in Sport, 13*(6), 618-623.

Brooks, G. A., Fahey, T. D., & Baldwin, K. M. (2005). *Exercise physiology : human bioenergetics and its applications* (4th edition ed.). McGraw-Hill.

Buchheit, M. (2014). Monitoring training status with HR measures: do all roads lead to Rome? *Frontiers In Physiology, 5*(73).

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://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=s3h&AN=99907346&site=eds-live&custid=s1145751

Buchheit, M., & Laursen, P. B. (2013). High-intensity interval training, solutions to the programming puzzle: Part I: Cardiopulmonary emphasis. *Sports Medicine, 43*, 313-338. https://doi.org/10.1007/s40279-013-0029-x

Buchheit, M., Morgan, W., Wallace, J., Bode, M., & Poulos, N. (2015). Physiological, psychometric, and performance effects of the Christmas break in Australian Football. *International Journal of Sports Physiology and Performance, 10*(1), 120-123.

Budgett, R. (1990). Overtraining syndrome. *British Journal of Sports Medicine, 24*(4), 231-236. https://doi.org/10.1136/bjsm.24.4.231

Busso, T., Carasso, C., & Lacour, J. R. (1991). Adequacy of a systems structure in the modeling of training effects on performance. *Journal of Applied Physiology, 71*(5), 2044-2049. https://doi.org/10.1152/jappl.1991.71.5.2044

Calvert, T. W., Banister, E. W., Savage, M. V., & Bach, T. (1976). A systems model of the effects of training on physical performance. *IEEE Transactions on Systems, Man and Cybernetics, 6*(2), 94-102. https://doi.org/10.1109/TSMC.1976.5409179

Colby, M. J., Dawson, B., Heasman, J., Rogalski, B., & Gabbett, T. J. (2014). Accelerometer and GPS-Derived running loads and injury risk in elite Australian footballers. *Journal of Strength and Conditioning Research, 28*(8), 2244-2252.

Corbett, D., Bartlett, J., O'Connor, F., Back, N., Torres-Ronda, L., & Robertson, S. (2017). Development of physical and skill training drill prescription systems for elite Australian Rules Football. *Science and Medicine in Football, 2*(1), 51-57.

Cormack, S. J., Mooney, M. G., Morgan, W., & McGuigan, M. R. (2013). Influence of neuromuscular fatigue on accelerometer load in elite Australian football players. *International Journal of Sports Physiology and Performance, 8*(4), 373-378.

Cormack, S. J., Newton, R. U., & McGuigan, M. R. (2008). Neuromuscular and endocrine responses of elite players to an Australian rules football match. *International Journal of Sports Physiology and Performance, 3*(3), 359-374.

Cormack, S. J., Smith, R. L., Mooney, M. M., Young, W. B., & O'Brien, B. J. (2014). Accelerometer load as a measure of activity profile in different standards of netball match play. *International Journal of Sports Physiology and Performance, 9*(2), 283-291.

Coutts, A. J., Quinn, J., Hocking, J., Castagna, C., & Rampinini, E. (2010). Match running performance in elite Australian Rules Football. *Journal of Science and Medicine in Sport, 13*(5), 543-548.

Coyle, E. F. (2000). Physical activity as a metabolic stressor. *American Journal of Clinical Nutrition, 72*(2), 512-520. https://doi.org/10.1093/ajcn/72.2.512s

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: A systematic review. *Sports Medicine, 43*(10), 1025. https://doi.org/10.1007/s40279-013-0069-2

Cunniffe, B., Baker, J. S., Davies, B., & Proctor, W. (2009). An evaluation of the physiological demands of elite rugby union using global positioning system tracking software. *Journal of Strength and Conditioning Research, 23*(4), 1195-1203. https://doi.org/10.1519/JSC.0b013e3181a3928b

Dai, B., Sorensen, C. J., Derrick, T. R., & Gillette, J. C. (2012). The effects of postseason break on knee biomechanics and lower extremity EMG in a stop-jump task: Implications for ACL injury. *Journal of Applied Biomechanics, 28*(6), 708-717.

Davis, I. V. H., Orzeck, T., & Keelan, P. (2007). Psychometric item evaluations of the Recovery-Stress Questionnaire for athletes. *Psychology of Sport and Exercise, 8*, 917-938. https://doi.org/10.1016/j.psychsport.2006.10.003

Day, M. L., McGuigan, M. R., Brice, G., & Foster, C. (2004). Monitoring exercise intensity during resistance training using the session RPE Scale. *Journal of Strength and Conditioning Research, 18*(2), 353-358.

deCunanan, A. J., DeWeese, B. H., Wagle, J. P., Carroll, K. M., Sausaman, R., Stone, M. H., Hornsby, W. G., Haff, G. G., Triplett, N. T., & Pierce, K. C. (2018). The general adaptation syndrome: A foundation for the concept of periodization. *Sports Medicine*, 1-11. https://doi.org/10.1007/s40279-017-0855-3

Delaney, J., Cummins, C., Compton, H., & Duthie, G. (2018a). Importance, reliability, and usefulness of acceleration measures in team sports. *Journal of Strength and Conditioning Research, 32*(12), 3485-3493. https://doi.org/10.1519/JSC.0000000000001849

Delaney, J. A., Duthie, G., Thornton, H. R., & Pyne, D. B. (2018b). Quantifying the relationship between internal and external work in team sports: development of a novel training efficiency index. *Science and Medicine in Football, 2*(2), 149-156.

Delaney, J. A., Duthie, G., Thornton, H. R., Scott, T. J., Gay, D., & Dascombe, B. J. (2015). 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., Thornton, H. R., Burgess, D. J., Dascombe, B. J., & Duthie, G. (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

Delaney, J. A., Thornton, H. R., Rowell, A. E., Dascombe, B. J., Aughey, R. J., & Duthie, G. (2018c). Modelling the decrement in running intensity within professional soccer players. *Science and Medicine in Football, 2*(2), 86-92. https://doi.org/10.1080/24733938.2017.1383623

Delves, R., Duthie, G., Ball, K., & Aughey, R. (2022). Applying common filtering processes to Global Navigation Satellite System-derived acceleration during team sport locomotion. *Journal of Sports Sciences, 40*(10), 1116-1126. https://doi.org/10.1080/02640414.2022.2051332

Delves, R. I. M., Aughey, R., Ball, K., & Duthie, G. (2021). The quantification of acceleration events in elite team sport: A systematic review. *Sports Medicine, 7*(1), 45. https://doi.org/10.1186/s40798-021-00332-8

Derman, W., Schwellnus, M. P., Lambert, M. I., Emms, M., Sinclair-Smith, C., Kirby, P., & Noakes, T. D. (1997). The 'worn-out athlete': A clinical approach to chronic fatigue in athletes. *Journal of Sports Sciences, 15*(3), 341-351.

Drew, M. K., & Finch, C. F. (2016). The relationship between training load and injury, illness and soreness: A systematic and literature review. *Sports Medicine 46*(6), 861-883.

Duthie, G. M., Robertson, S., & Thornton, H. R. (2021). A GNSS-based method to define athlete manoeuvrability in field-based team sports. *PLoS ONE, 16*(11), 0260363. https://doi.org/10.1371/journal.pone.0260363

Ellens, S., Middleton, K., Gastin, P. B., & Varley, M. C. (2022). Techniques to derive and clean acceleration and deceleration data of athlete tracking technologies in team sports: A scoping review. *Journal of Sports Sciences, 40*(16), 1772-1800.

Esmaeili, A., Clifton, P., & Aughey, R. J. (2020). A league-wide evaluation of factors influencing match activity profile in elite Australian football. *6*(2). https://doi.org/10.3389/fspor.2020.579264

Esmaeili, A., Stewart, A. M., Hopkins, W. G., Elias, G. P., Lazarus, B. H., Rowell, A. E., & Aughey, R. J. (2018). Normal variability of weekly musculoskeletal screening scores and the influence of training load across an Australian football league season. *Frontiers In Physiology, 9*.

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 and Coaching, 3*(4), 489-499.

Fitz-Clarke, J. R., Morton, R. H., & Banister, E. W. (1991). Optimizing athletic performance by influence curves. *Journal of Applied Physiology, 71*(3), 1151-1158. https://doi.org/10.1152/jappl.1991.71.3.1151

Foster, C. (1998). Monitoring training in athletes with reference to overtraining syndrome. *Med Sci Sports Exerc, 30*(7), 1164-1168.

Foster, C., Daines, E., Hector, L., Snyder, A. C., & Welsh, R. (1996). Athletic performance in relation to training load. *Wis Med J, 95*(6), 370-374.

Fox, J. L., Scanlan, A., Sargent, C., & Stanton, R. (2020). A survey of player monitoring approaches and microsensor use in basketball. *Journal of Human Sport and Exercise, 15*(1), 230-240.

Franks, I. M., & Miller, G. (1986). Eyewitness testimony in sport. . *Journal of Sport Behavior, 9*(1), 38-45.

Frencken, W. G. P., Lemmink, K. A. P. M., & Delleman, N. J. (2010). Soccer-specific accuracy and validity of the local position measurement (LPM) system. *Journal of Science and Medicine in Sport, 13*(6), 641-645.

Gabbett, T. (2006a). A comparison of physiological and anthropometric characteristics among playing positions in sub-elite Rugby League players. *Journal of Sports Sciences, 24*(12), 1273-1280.

Gabbett, T., & Domrow, N. (2007). Relationships between training load, injury, and fitness in sub-elite collision sport athletes. *Journal of Sports Sciences, 25*(13), 1507-1519.

Gabbett, T., & Godbolt, R. (2010). Training injuries in professional Rugby League. *Journal of Strength and Conditioning Research, 24*(7), 1948-1953. https://doi.org/10.1519/JSC.0b013e3181ddad65

Gabbett, T., Jenkins, D., & Abernethy, B. (2010). Physical collisions and injury during professional rugby league skills training. *Journal of Science and Medicine in Sport, 13*(6), 578-583.

Gabbett, T. J. (2004). Influence of training and match intensity on injuries in rugby league. *Journal of Sports Sciences, 22*(5), 409-417.

Gabbett, T. J. (2006b). Skill-based conditioning games as an alternative to traditional conditioning for Rugby League players. *Journal of Strength and Conditioning Research, 20*(2), 309-315.

Gabbett, T. J. (2015). Relationship between accelerometer load, collisions, and repeated high-intensity effort activity in Rugby League players. *Journal of Strength and Conditioning Research, 29*(12), 3424-3431. https://doi.org/10.1519/JSC.0000000000001017

Gabbett, T. J. (2016). The training-injury prevention paradox: should athletes be training smarter and harder? *British Journal of Sports Medicine, 50*(5), 273-280.

Gabbett, T. J., & Mulvey, M. J. (2008). Time-motion analysis of small-sided training games and competition in elite women soccer players. *Journal of Strength and Conditioning Research, 22*(2), 543-552. https://doi.org/10.1519/JSC.0b013e3181635597

Gabbett, T. J., Polley, C., Dwyer, D. B., Kearney, S., & Corvo, A. (2014). Influence of field position and phase of play on the physical demands of match-play in professional Rugby League forwards. *Journal of Science and Medicine in Sport, 17*(5), 556-561. https://doi.org/https://doi.org/10.1016/j.jsams.2013.08.002

Gallo, T., Cormack, S., Gabbett, T., Williams, M., & Lorenzen, C. (2015). Characteristics impacting on session rating of perceived exertion training load in Australian footballers. *Journal of Sports Sciences, 33*(5), 467-475.

Gallo, T. F., Cormack, S. J., Gabbett, T. J., & Lorenzen, C. H. (2016). Pre-training perceived wellness impacts training output in Australian Football players. *Journal of Sports Sciences, 34*(15), 1445-1451.

Gallo, T. F., Cormack, S. J., Lorenzen, C. H., & Gabbett, T. J. (2017). Self-reported wellness profiles of professional Australian Football players during the competition phase of the season. *Journal of Strength and Conditioning Research, 31*(2), 495-502.

Gastin, P. B., Meyer, D., & Robinson, D. (2013). Perceptions of wellness to monitor adaptive responses to training and competition in elite Australian Football. *Journal of Strength and Conditioning Research, 27*(9), 2518-2526.

Gray, A., Jenkins, D., Andrews, M., Taaffe, D., & Glover, M. (2010). Validity and reliability of GPS for measuring distance travelled in field-based team sports. *Journal of Sports Sciences, 28*(12), 1319-1325.

Gray, A. J., & Jenkins, D. G. (2010). Match analysis and the physiological demands of Australian Football. *Sports Medicine, 40*(4), 347-360.

Grira, N., Crucianu, M., & Boujemaa, N. (2005). Unsupervised and semi-supervised clustering: A brief survey. *A Review of Machine Learning Techniques for Processing Multimedia Content*.

Gucciardi, D., Gordon, S., & Dimmock, J. (2008). Towards an understanding of mental toughness in Australian Football. *Journal of Applied Sport Psychology, 20*(3), 261-281.

Halouani, J., Chtourou, H., Gabbett, T. I. M., Chaouachi, A., & Chamari, K. (2014). Small-sided games in team sports training: A brief review. *Journal of Strength and Conditioning Research, 28*(12), 3594-3618.

Halson, S. (2014). Monitoring training load to understand fatigue in athletes. *Sports Medicine, 44*(2), 139-147.

Hawley, J. A., Burke, L. M., Phillips, S. M., & Spriet, L. L. (2011). Nutritional modulation of training-induced skeletal muscle adaptations. *Journal of Applied Physiology, 110*(3), 834-845.

Heasman, J., Dawson, B., Berry, J., & Stewart, G. (2008). Development and validation of a player impact ranking system in Australian Football. *International Journal of Performance Analysis in Sport, 8*(3), 156-171.

[Record #372 is using a reference type undefined in this output style.]

Hill-Haas, S. V., Dawson, B., Impellizzeri, F. M., & Coutts, A. J. (2011). Physiology of small-sided games training in football: A systematic review. *Sports Medicine, 41*(3), 199. https://doi.org/10.2165/11539740-000000000-00000

Hiscock, D., Dawson, B., Heasman, J., & Peeling, P. (2012). Game movements and player performance in the Australian Football League. *International Journal of Performance Analysis in Sport, 12*(3), 531-545.

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc, 41*(1), 3-13. https://doi.org/10.1249/MSS.0b013e31818cb278

Hoppe, M. W., Baumgart, C., Polglaze, T., & Freiwald, J. (2018). Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PLoS ONE, 13*(2), e0192708.

Impellizzeri, F. M., & Bizzini, M. (2012). Systematic review and meta-analysis: a primer. *International Journal of Sports Physical Therapy, 7*(5), 493-503.

Jeffries, A. C., Marcora, S. M., Coutts, A. J., Wallace, L., McCall, A., & Impellizzeri, F. M. (2022). Development of a revised conceptual framework of physical training for use in research and practice. *Sports Medicine, 52*(4), 709-724. https://doi.org/10.1007/s40279-021-01551-5

Jennings, D., Cormack, S., Coutts, A., Boyd, L., & Aughey, R. (2010a). The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *International Journal of Sports Physiology and Performance, 5*(3), 328-341. https://doi.org/10.1123/ijspp.5.3.328

Jennings, D., Cormack, S., Coutts, A., Boyd, L., & Aughey, R. (2010b). Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology and Performance, 5*(4), 565-569. https://doi.org/10.1123/ijspp.5.4.565

Johnston, R., Compton, H., Wade, J., Devlin, P., & Duthie, G. (2020). The distribution of match activities relative to the maximal mean intensities in professional Rugby League and Australian football. *Journal of Strength and Conditioning Research, 36*(5), 1360-1366. https://doi.org/10.1519/JSC.0000000000003613

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.

Johnston, R. D., Gabbett, T. J., Jenkins, D. G., & Hulin, B. T. (2015a). Influence of physical qualities on post-match fatigue in rugby league players. *Journal of Science and Medicine in Sport, 18*(2), 209-213. https://doi.org/10.1016/j.jsams.2014.01.009

Johnston, R. J., Watsford, M. L., Austin, D., Pine, M. J., & Spurrs, R. W. (2015b). Player acceleration and deceleration profiles in professional Australian Football. *Journal of Sports Medicine and Physical Fitness, 55*(9), 931-939.

Johnston, R. J., Watsford, M. L., Austin, D. J., Pine, M. J., & Spurrs, R. W. (2015c). An examination of the relationship between movement demands and rating of perceived exertion in Australian Footballers. *Journal of Strength and Conditioning Research, 29*(7), 2026-2033.

Johnston, R. J., Watsford, M. L., Austin, D. J., Pine, M. J., & Spurrs, R. W. (2015d). Movement demands and metabolic power comparisons between elite and subelite Australian footballers. *The Journal of Strength & Conditioning Research, 29*(10), 2738-2744.

Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J., & Spurrs, R. W. (2014). Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *Journal of Strength and Conditioning Research, 28*(6), 1649-1655. https://doi.org/10.1519/JSC.0000000000000323

Johnston, R. J., Watsford, M. L., Pine, M. J., Spurrs, R. W., Murphy, A., & Pruyn, E. C. (2012). Movement demands and match performance in professional Australian Football. *International Journal of Sports Medicine, 33*(2), 89-93.

Jones, A. M., & Carter, H. (2000). The effect of endurance training on parameters of aerobic fitness. *Sports Medicine, 29*(6), 373. https://doi.org/10.2165/00007256-200029060-00001

Kellmann, M. (2002). *Enhancing recovery : preventing underperformance in athletes*. Human Kinetics.

Kellmann, M. (2010). Preventing overtraining in athletes in high-intensity sports and stress/recovery monitoring. *Scandinavian Journal of Medicine & Science in Sports, 20*, 95-102.

Kellmann, M., & Kallus, K. W. (2001). *Recovery-stress questionnaire for athletes : user manual*. Champaign, IL : Human Kinetics, 2001.

Kempton, T., Sirotic, A. C., Rampinini, E., & Coutts, A. J. (2015). Metabolic power demands of Rugby League match play. *International Journal of Sports Physiology and Performance, 10*(1), 23-28. https://doi.org/10.1123/ijspp.2013-0540

Kentta, G., & Hassmen, P. (1998). Overtraining and recovery. A conceptual model. *Sports Medicine, 26*(1), 1-16.

Locale Kenttä, G., Hassmén, P., & Raglin, J. S. (2006). Mood state monitoring of training and recovery in elite kayakers. *European Journal Of Sport Science, 6*(4), 245-253.

Kouzaki, M., Masani, K., Akima, H., Shirasawa, H., Fukuoka, H., Kanehisa, H., & Fukunaga, T. (2007). Effects of 20-day bed rest with and without strength training on postural sway during quiet standing. *Acta physiologica (Oxford, England), 189*(3), 279-292. https://doi.org/10.1111/j.1748-1716.2006.01642.x

Lambert, M., & Borresen, J. (2010). Measuring training load in sports. *International Journal of Sports Physiology and Performance, 5*, 406-411. https://doi.org/10.1123/ijspp.5.3.406

Lambert, M., & Borresen, J. (2016). A theoretical basis of monitoring fatigue: A practical approach for coaches. *Track Coach*(214), 6822-6834.

Lambert, M. I., Viljoen, W., Bosch, A., Pearce, A. J., & Sayers, M. (2008). The Olympic textbook of medicine in sport. In M. Schwellnus (Ed.), *Encyclopaedia of sports medicine* (Vol. 14). Wiley-Blackwell.

Lan, M. F., Lane, A., Roy, J., & Hanin, N. (2012). Validity of the Brunel mood scale for use with Malaysian athletes. *Journal of Sports Science & Medicine, 11*, 131-135.

Larsson, P. (2003). Global positioning system and sport-specific testing. *Sports Medicine, 33*(15). https://doi.org/10.2165/00007256-200333150-00002

Lazarus, B. H., Stewart, A., White, K. M., Rowell, A. E., Esmaeili, A., Hopkins, W., & Aughey, R. (2017). Proposal of a global training load measure predicting match performance in an elite team sport. *Frontiers In Physiology, 8*.

Lehmann, M., Foster, C., Gastmann, U., Keizer, H., & Steinacker, J. M. (1999). *Overload, performance incompetence, and regeneration in sport*. Plenum Publishers.

LeUnes, A., & Burger, J. (1998). Bibliography on the Profile of Mood States in sport and exercise psychology research, 1971-1998. *Journal of Sport Behavior, 21*(1), 53.

Lochbaum, M., Zanatta, T., Kirschling, D., & May, E. (2021). The Profile of Moods States and athletic performance: A meta-analysis of published studies. *European Journal of Investigation in Health, Psychology and Education, 11*(5), 50-70. https://doi.org/10.3390/ejihpe11010005

Lorenzen, C., Williams, M. D., Turk, P. S., Meehan, D. L., & Kolsky, D. J. C. (2009). Relationship between velocity reached at VO2 max and time-trial performances in elite Australian Rules Footballers. *International Journal of Sports Physiology and Performance, 4*(3), 408-411.

Los Arcos, A., Martínez-Santos, R., Yanci, J., Mendiguchia, J., & Méndez-Villanueva, A. (2015). Negative associations between perceived training load, volume and changes in physical fitness in professional soccer players. *Journal of Sports Science and Medicine, 14*(2), 394-401.

Los Arcos, A., Mendez-Villanueva, A., & Martínez-Santos, R. (2017). In-season training periodization of professional soccer players. *Biology of sport, 34*(2), 149-155. https://doi.org/10.5114/biolsport.2017.64588

Lovell, T. W. j., Sirotic, A. C., Impellizzeri, F. M., & Coutts, A. J. (2013). Factors affecting perception of effort (Session rating of perceived exertion) during Rugby League training. *International Journal of Sports Physiology and Performance, 8*(1), 62-69.

Mageau, G. A., & Vallerand, R. J. (2003). The coach-athlete relationship: a motivational model. *Journal of Sports Sciences, 21*(11), 883-904.

Magill, R. A. (2021). *Motor learning and control : concepts and applications* (Twelth ed.). New York: McGraw-Hill Education.

Mann, T., Lamberts, R., & Lambert, M. (2014). High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Medicine, 44*(8), 1113-1124.

Martínez, J. A., & Martínez, L. (2011). A stakeholder assessment of basketball player evaluation metrics. *Journal of Human Sport and Exercise, 6*(1), 153-183.

McGuigan, M. R., Cormack, S., & Newton, R. U. (2009). Long-term power performance of elite Australian Rules Football players. *Journal of Strength and Conditioning Research, 23*(1), 26-32. https://doi.org/10.1519/JSC.0b013e31818753ca

McGuigan, M. R., Doyle, T. L. A., Newton, M., Edwards, D. J., Nimphius, S., & Newton, R. U. (2006). Eccentric utilization ratio: Effect of sport and phase of training. *Journal of Strength and Conditioning Research, 20*(4), 992-995.

McGuigan, M. R., Wright, G. A., & Fleck, S. J. (2012). Strength training for athletes: Does it really help sports performance? *International Journal of Sports Physiology and Performance, 7*(1), 2-6.

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 and Coaching, 13*(6), 1064-1071.

McIntosh, S., Kovalchik, S., & Robertson, S. (2019). Comparing subjective and objective evaluations of player performance in Australian Rules football. *PLoS ONE, 14*(8), 1-16. https://doi.org/10.1371/journal.pone.0220901

McLaren, S. J., Coutts, A. J., & Impellizzeri, F. M. (2022). Perception of Effort and Subjective Monitoring. In N.-N. S. C. Association, D. N. French, & L. T. Ronda (Eds.), *NSCA'S Essentials of sport science*. Human Kinetics.

McLaren, S. J., Macpherson, T. W., Coutts, A. J., Hurst, C., Spears, I. R., & Weston, M. (2018). The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis. *Sports Medicine, 48*(3), 641-658.

McLean, B. D., Coutts, A. J., Kelly, V., McGuigan, M. R., & Cormack, S. J. (2010). Neuromuscular, endocrine, and perceptual fatigue responses during different length between-match microcycles in professional Rugby League players. *International Journal of Sports Physiology and Performance, 5*(3), 367-383.

Meister, S., Faude, O., Ammann, T., Schnittker, R., & Meyer, T. (2013). Indicators for high physical strain and overload in elite football players. *Scandinavian Journal of Medicine and Science in Sports, 23*(2), 156-163.

Menaspà, M. J., Menaspà, P., Clark, S. A., & Fanchini, M. (2017). Validity of the online athlete management system to assess training load. *International Journal of Sports Physiology and Performance*, 1-17. https://doi.org/10.1123/ijspp.2017-0379

Montgomery, P. G., Pyne, D. B., & Minahan, C. L. (2010). The physical and physiological demands of basketball training and competition. *International Journal of Sports Physiology and Performance, 5*(1), 75-86.

Mooney, M., Cormack, S., O'Brien, B., & Coutts, A. J. (2013). Do physical capacity and interchange rest periods influence match exercise-intensity profile in Australian Football? *International Journal of Sports Physiology and Performance, 8*(2), 165-172.

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.

Moreira, A., Bilsborough, J. C., Sullivan, C. J., Cianciosi, M., Saldanha Aoki, M., & 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

Mujika, I., Chatard, J.-C., Busso, T., Geyssant, A., Barale, F., & Lacoste, L. (1995). *Effects of training on performance in competitive swimming* (Vol. 20). https://doi.org/10.1139/h95-031

Mujika, I., Halson, S., Burke, L. M., Balagué, G., & Farrow, D. (2018). An integrated, multifactorial approach to periodization for optimal performance in individual and team sports. *International Journal of Sports Physiology and Performance, 13*(5), 538-561.

Mujika, I., & Padilla, S. (2000). Detraining: Loss of training-induced physiological and performance adaptations. Part I: Short term insufficient training stimulus. *Sports Medicine, 30*(2), 79.

Mujika, I., & Padilla, S. (2001). Muscular characteristics of detraining in humans. *Med Sci Sports Exerc, 33*(8), 1297-1303.

Mujika, I., Padilla, S., Pyne, D., & Busso, T. (2004). Physiological changes associated with the pre-event taper in athletes. *Sports Medicine, 34*(13), 891.

Myers, V. R., Wells, G. D., McKillop, A. L., Fraser, S. J., & Abel, J. M. (2017). Physiological and psychological adaptations during taper in competitive swimmers. *International Journal of Sports Science and Coaching, 12*(4), 481-494.

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.

Ogris, G., Leser, R., Horsak, B., Kornfeind, P., Heller, M., & Baca, A. (2012). Accuracy of the LPM tracking system considering dynamic position changes. *Journal of Sports Sciences, 30*(14), 1503-1511.

Orchard, J. (2012, June 20). Who is to blame for all the football injuries? *guest blog*. http://blogs.bmj.com/bjsm/2012/06/20/who-is-to-blame-for-all-the-football-injuries/

Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R., & Di Prampero, P. E. (2010). Energy cost and metabolic power in elite soccer: A new match analysis approach. *American College of Sports Medicine, 42*(1), 170-178.

Philippe, V., Michel, N., Guillaume, M., & Laurent, M. (2017). Changes of swimmers' emotional states during the preparation of national championship: Do recovery-stress states matter? *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.01043

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.

Prud'homme, D., Bouchard, C., Leblanc, C., Landry, F., & Fontaine, E. (1984, Oct). Sensitivity of maximal aerobic power to training is genotype-dependent. *Med Sci Sports Exerc, 16*(5), 489-493.

Pyne, D. B., Gardner, A. S., Sheehan, K., & Hopkins, W. G. (2005). Fitness testing and career progression in AFL football. *Journal of Science and Medicine in Sport, 8*(3), 321-332.

Rampinini, E., Alberti, G., Fiorenza, M., Riggio, M., Sassi, R., Borges, T. O., & Coutts, A. J. (2015). Accuracy of GPS devices for measuring high-intensity running in field-based team sports. *International Journal of Sports Medicine, 36*(1), 49-53. https://doi.org/10.1055/s-0034-1385866

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.

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.

Rowell, A., E. , Aughey, R., J. , Clubb, J., & Cormack, S., J. . (2018). A standardized small sided game can be used to monitor neuromuscular fatigue in professional A-League Football players. *Frontiers In Physiology, 9*. https://doi.org/10.3389/fphys.2018.01011

Rushall, B. S. (1990). A tool for measuring stress tolerance in elite athletes. *Journal of Applied Sport Psychology, 2*(1), 51-66.

Ryan, S., Coutts, A. J., Hocking, J., & Kempton, T. (2017). Factors affecting match running performance in professional Australian football. *International Journal of Sports Physiology and Performance, 12*(9), 1199-1204.

Saha, I., Maulik, U., Bandyopadhyay, S., & Plewczynski, D. (2011). Unsupervised and supervised learning approaches together for microarray analysis. *Fundamenta Informaticae, 106*, 45-73.

Sánchez-Díaz, S., Yanci, J., Castillo, D., Scanlan, A. T., & Raya-González, J. (2020). Effects of nutrition education interventions in team sport players. A systematic review. *Nutrients, 12*(12), 3664. https://www.mdpi.com/2072-6643/12/12/3664

Sathyan, T., Shuttleworth, R., Hedley, M., & Davids, K. (2012). Validity and reliability of a radio positioning system for tracking athletes in indoor and outdoor team sports. *Behavior Research Methods, 44*(4), 1108. https://doi.org/10.3758/s13428-012-0192-2

Saw, A. E., Main, L. C., & Gastin, P. B. (2015a). Monitoring athletes through self-report: factors influencing implementation. *Journal of Sports Science and Medicine, 14*(1), 137-146.

Saw, A. E., Main, L. C., & Gastin, P. B. (2015b). Role of a self-report measure in athlete preparation. *Journal of Strength and Conditioning Research, 29*, 685-691.

Scanlan, A. T., Tucker, P. S., Dalbo, V. J., & Wen, N. (2014). The relationships between internal and external training load models during basketball training. *Journal of Strength and Conditioning Research, 28*(9), 2397-2405. https://doi.org/10.1519/JSC.0000000000000458

Scharhag-Rosenberger, F., Walitzek, S., Kindermann, W., & Meyer, T. (2012). Differences in adaptations to 1 year of aerobic endurance training: individual patterns of nonresponse. *Scandinavian Journal of Medicine and Science in Sports, 22*(1), 113-118.

Schumaker, R. P., Solieman, O. K., & Chen, H. (2010). *Sports data mining. Integrated series in information systems* (Vol. 26). New York, NY: Springer.

Scott, M. T. U., Scott, T. J., & Kelly, V. G. (2016). The validity and reliability of global positioning systems in team sport: A brief review. *Journal of Strength and Conditioning Research, 30*(5), 1470-1490. https://doi.org/10.1519/JSC.0000000000001221

Scott, T. J., Black, C. R., Quinn, J., & Coutts, A. J. (2013). Validity and reliability of the session-RPE method for quantifying training in Australian Football: a comparison of the CR10 and CR100 scales. *Journal of Strength and Conditioning Research, 27*(1), 270-276.

Seidl, T., Czyz, T., Spandler, D., Franke, N., & Lochmann, M. (2016). Validation of football's velocity provided by a radio-based tracking system. *Procedia Engineering, 147*, 584-589. https://doi.org/10.1016/j.proeng.2016.06.244

Selmi, O., Ben khalifa, W., Zouaoui, M., Azaiez, F., & Bouassida, A. (2018). High intensity interval training negatively affects mood state in professional athletes. *Science et Sports, 33*(4), 151-157. https://doi.org/10.1016/j.scispo.2018.01.008

Siegle, M., Stevens, T., & Lames, M. (2013). Design of an accuracy study for position detection in football. *Journal of Sports Sciences, 31*(2), 166-172.

Slattery, K. M., Wallace, L. K., Bentley, D. J., & Coutts, A. J. (2012). Effect of training load on simulated team sport match performance. *Applied Physiology, Nutrition and Metabolism, 37*(2), 315-322.

Sports, F. (2018). *AFL Best and Fairest Winners 2018: Who won your team's club champion award?*

Stanley, J., Peake, J. M., & Buchheit, M. (2013). Cardiac parasympathetic reactivation following exercise: implications for training prescription. *Sports Medicine, 43*(12), 1259-1277.

Stevens, T. G. A., De Ruiter, C. J., Van Niel, C., Van De Rhee, R., Beek, P. J., & Savelsbergh, G. J. P. (2014). Measuring acceleration and deceleration in soccer-specific movements using a local position measurement (lpm) system. *International Journal of Sports Physiology and Performance, 9*(3), 446-456. https://doi.org/10.1123/IJSPP.2013-0340

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.

Swarbrick, M. (2006). A wellness approach. *Psychiatric Rehabilitation Journal, 29*(4), 311-314.

Talabis, M. R. M., McPherson, R., Miyamoto, I., Martin, J. L., & Kaye, D. (2015). Chapter 1 - Analytics Defined. In M. R. M. Talabis, R. McPherson, I. Miyamoto, J. L. Martin, & D. Kaye (Eds.), *Information Security Analytics* (pp. 1-12). Syngress.

Tavana, M., Azizi, F., Azizi, F., & Behzadian, M. (2013). A fuzzy inference system with application to player selection and team formation in multi-player sports [Article]. *Sport Management Review, 16*(1), 97-110. https://doi.org/10.1016/j.smr.2012.06.002

Taylor, K.-L., Chapman, D., Cronin, J., Newton, M., & Gill, N. (2012). Fatigue monitoring in high performance sport: A survey of current trends. *Journal of Australian Strength and Conditioning, 20*, 12-23.

Thornton, H., R., Armstrong, C., R. , Rigby, A., Minahan, C., L. , Johnston, R., D. , & Duthie, G., M. (2020). Preparing for an Australian Football League women's league season. *Frontiers in Sports and Active Living, 2*, 1-10. https://doi.org/10.3389/fspor.2020.608939

Thornton, H. R., Armstrong, C. R., Gamble, T., Rigby, A., Johnston, R. D., & Duthie, G. M. (2022). Quantifying the movement characteristics of Australian Football League women's competition. *Journal of Strength and Conditioning Research, 36*(12), 3415. https://doi.org/10.1519/JSC.0000000000003810

Thornton, H. R., Nelson, A. R., Delaney, J. A., Serpiello, F. R., & Duthie, G. M. (2019). Interunit reliability and effect of data-processing methods of global positioning systems. *International Journal of Sports Physiology and Performance, 14*(4), 432-438. https://doi.org/10.1123/ijspp.2018-0273

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).

Torres-Ronda, L., & Schelling, X. (2017). Critical process for the implementation of technology in sport organizations. *Strength and Conditioning Journal, 39*(6), 54-59. https://doi.org/10.1519/SSC.0000000000000339

Trninić, S., Papić, V., Trninić, V., & Vukicevic, D. (2008). Player selection procedures in team sports games. *Acta Kinesiologica, 2*(1), 24-28.

Vanrenterghem, J., Nedergaard, N. J., Robinson, M. A., & Drust, B. (2017). Training load monitoring in team sports: A novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Medicine, 47*(11), 2135-2142. https://doi.org/10.1007/s40279-017-0714-2

Varley, M. C., Elias, G., & Aughey, R. (2012a). 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., Fairweather, I. H., & Aughey, R. J. (2012b). Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *Journal of Sports Sciences, 30*(2), 121-127. https://doi.org/10.1080/02640414.2011.627941

Varley, M. C., Gabbett, T., & Aughey, R. (2014). Activity profiles of professional soccer, rugby league and Australian football match play. *Journal of Sport Sciences, 32*(20), 1858-1866. https://doi.org/10.1080/02640414.2013.823227

Varley, M. C., Jaspers, A., Helsen, W. F., & Malone, J. J. (2017). Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology. *International Journal of Sports Physiology and Performance, 12*(8), 1059-1068. https://doi.org/10.1123/ijspp.2016-0534

Vinokur, A., Oksenberg, L., & Cannell, C. F. (1979). Effects of feedback and reinforcement on the report of health information. In C. F. Cannell, L. Oksenberg, & J. M. Converse (Eds.), *Experiments in interviewing techniques*.

Vollaard, N. B. J., Timmons, J. A., Constantin-Teodosiu, D., Greenhaff, P. L., Fredriksson, K., Rooyackers, O., Jansson, E., & Sundberg, C. J. (2009). Systematic analysis of adaptations in aerobic capacity and submaximal energy metabolism provides a unique insight into determinants of human aerobic performance. *Journal of Applied Physiology, 106*(5), 1479-1486.

Wallace, L., Coutts, A., Bell, J., Simpson, N., & Slattery, K. (2008). Using session-RPE to monitor training load in swimmers. *Strength and Conditioning Journal, 30*(6), 72-76.

Weaving, D., Jones, B., Marshall, P., Till, K., & Abt, G. (2017). Multiple measures are needed to quantify training loads in professional Rugby League. *International Journal of Sports Medicine, 38*(10), 735-740.

Weaving, D., Marshall, P., Earle, K., Nevill, A., & Abt, G. (2014). Combining internal and external training load measures in professional Rugby League. *International Journal of Sports Physiology and Performance, 9*(6), 905-912.

Weaving, D., Young, D., Riboli, A., Jones, B., & Coratella, G. (2022). The maximal intensity period: Rationalising its use in team sports practice. *Sports Medicine - Open, 8*(1), 128. https://doi.org/10.1186/s40798-022-00519-7

Weston, M., Siegler, J., Bahnert, A., McBrien, J., & Lovell, R. (2015). The application of differential ratings of perceived exertion to Australian Football League matches. *Journal of Science and Medicine in Sport, 18*(6), 704-708.

Wickham, H. (2016). *Ggplot2 : elegant graphics for data analysis* (Second ed.). Springer.

Wilke, C. (2019). *Fundamentals of data visualization : A primer on making informative and compelling figures* (First ed.). O'Reilly Media.

Wing, C., Hart, N. H., Ma'ayah, F., & Nosaka, K. (2021). Evaluating match running performance in elite Australian football: A narrative review. *BMC Sports Science, Medicine and Rehabilitation, 13*(1), 1-14.

Wisbey, B., Montgomery, P. G., Pyne, D. B., & Rattray, B. (2010). Quantifying movement demands of AFL football using GPS tracking. *Journal of Science and Medicine in Sport, 13*(5), 531-536.

Wood, R. E., Hayter, S., Rowbottom, D., & Stewart, I. (2005). Applying a mathematical model to training adaptation in a distance runner [Original Paper]. *European Journal Of Applied Physiology, 94*(3), 310. https://doi.org/10.1007/s00421-005-1319-2

Wright, C., Jones, B., Atkins, S., & Todd, J. (2013). The role of performance analysts within the coaching process: Performance Analysts Survey 'The role of performance analysts in elite football club settings'. *International Journal of Performance Analysis in Sport, 13*(1), 240-261. https://doi.org/10.1080/24748668.2013.11868645

Wundersitz, D. W. T., Josman, C., Gupta, R., Netto, K. J., Gastin, P. B., & Robertson, S. (2015). Classification of team sport activities using a single wearable tracking device. *Journal of Biomechanics, 48*(15), 3975-3981.

Young, W. B. (2006). Transfer of strength and power training to sports performance. *International Journal of Sports Physiology and Performance, 1*(2), 74-83.

Young, W. B., Newton, R. U., Doyle, T. L. A., Chapman, D., Cormack, S., Stewart, C., & Dawson, B. (2005). Physiological and anthropometric characteristics of starters and non-starters and playing positions in elite Australian Rules Football: a case study. *Journal of Science and Medicine in Sport, 8*(3), 333-345.