Quantifying & Characterising Peak Intensities of Professional Rugby using GPS & Accelerometers

by

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Bachelor of Exercise and Health Science (Honours)

A thesis submitted in fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

The use of wearable technology in team sports to quantify physical activity during training and competition is now ubiquitous. Coaches typically use information derived from player tracking technologies such as Global Positioning Systems (GPS) to prescribe and monitor training. If coaches prepare players relative to the average intensity of competition, they will be underprepared for the rigors of competiton. Despite the majority of team sport competition being spent at submaximal intensity, high-intensity activities are often aligned with key events that determine match outcome. Therefore, coaches should periodically expose players to the physical worst-case scenarios of competition, whilst concurrently training tactical and technical qualities so that players may thrive and not simply survive during these intense periods of match-play. Understanding the utility of player tracking technologies, measures and analysis techniques for identifying and quantifying peak periods of competition enables coaches to more accurately interpret and use the data to inform match-specific training practices. This series of studies sought to identify, quantify and characterise the most intense periods of professional rugby competitions and periods thereafter with the aim of helping coaches to prescribe and monitor training that is more representative of competition and aid match-day tactical decisions.

Despite tri-axial accelerometers being embedded within GPS devices, their use for quantifying intense periods of team sport movement in research and practice is limited. Study one (Chapter 3) found that accelerometers outperformed GPS in quantifying positional and match-half peak intensity differences during rugby competition, identified using rolling epoch analysis. Accelerometers provided meaningful additional information

to GPS technology that may aid practitioners in physically preparing and monitoring rugby players. Study two (Chapter 4) assessed the sensitivity, reliability and convergent validity of GPS and accelerometer measures for quantifying peak intensities of rugby. The poor sensitivity and low reliability of GPS and accelerometer measures implied that rugby players need to be monitored across many matches to obtain adequate precision for assessing individuals. Study three (Chapter 5) examined factors that may influence peak intensities of rugby competition, such as exercise duration, positional group, match-half, level of competition, within-season trends and time spent on field. Findings provide professional rugby coaches with duration- and position-specific intensities to aid prescription and monitoring of match-specific training, whilst improving broader understanding of factors that influence player movement intensity. Study four (Chapter 6) sequentially tracked the time-course of exercise intensity declines post the most intense periods of rugby competition using novel analysis. Exercise intensity declined sharply post the most intense periods of competition, falling below the match average intensity and rarely returning shortly thereafter. Findings may inform tactical match decisions and match representative training prescription and monitoring. Finally, study five (Chapter 7) established that professional rugby peak intensities of competition can be accurately predicted from exercise duration using power law statistical modelling, irrespective of playing position, match-half, level of competition or measure of exercise intensity. Novel insights on model prediction error as well as the patterns of error as a function of time may assist coaches to accurately interpret and use power law to prescribe and monitor match-specific training.

STUDENT DECLARATION

I, Samuel Thomas Howe, declare that the PhD thesis entitled "Quantifying & Characterising the Peak Intensities of Professional Rugby using GPS & Accelerometers" is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature: [redacted] **Date:** 28/4/2020

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This thesis is dedicated to the life and memory of my father

Dr Glen Michael Howe

ABBREVIATIONS

General

EPOC	excess post-exercise oxygen consumption
GAS	general adaptation syndrome
SSG	small-sided games
$\dot{V}O_2max$	maximal oxygen uptake

Measurement

au	arbitrary units
cm	centimetre
COM	centre of mass
DOP	dilution of precision
g	gravitational acceleration
HDOP	horizontal dilution of precision
hr	hour
Hz	Hertz
$kcal.min^{-1}$	kilocalorie per minute
kg	kilogram
km	kilometre
$km{\cdot}h^{-1}$	kilometres per hour
min	minute
$m{\cdot}min^{-1}$	metres per minute
$m{\cdot}s^{-1}$	metres per second
s	second

$W \cdot kg^{-1}$	Watts per kilogram

Measurement systems

GPS	Global Positioning Systems
LPS	local positioning system
MEMS	micro-electrical-mechanical system
TMA	time-motion analysis

Sports leagues

AFL	Australian Football League
EPL	English Premier League
NFL	National Football League
NRC	National Rugby Championship
NRL	National Rugby League
S15	Super 15 Rugby

Physical activity

HS	high-speed
PlayerLoad^{TM}	tri-axial accelerometer-derived external load
PlayerLoad^{TM}Slow	PlayerLoad^{TM} at movement speeds below $2 m.s^{-1}$
RHIE	repeated high-intensity efforts

Statistical

CV	coefficient of variation
CL	compatibility limit
CI	compatibility interval
ES	effect size

ICC	intraclass correlation coefficient
LoA	limits of agreement
MBD	magnitude-based decisions
p	probability value
r	Pearson's correlation coefficient
R^2	Pearson’s r squared, coefficient of determination
SD	standard deviation
SEE	standard error of the estimate
SWD	smallest worthwhile difference
TE	typical error
TEM	typical error of measurement

Symbols

%	percentage
~	approximately
<	less than
>	greater than
≤	less than or equal to
≥	greater than or equal to
±	plus/minus
↑	increase
↓	decrease

PUBLICATIONS

Chapter 3

1. S. T. Howe, R. J. Aughey, W. G. Hopkins, A. M. Stewart and B. P. Cavanagh. (2017). Quantifying important differences in athlete movement during collision-based team sports: Accelerometers outperform Global Positioning Systems. *IEEE International Symposium on Inertial Sensors and Systems* (INERTIAL), pp. 1-4. DOI: 10.1109/ISISS.2017.7935655

Chapter 4

2. S. T. Howe, R. J. Aughey, W. G. Hopkins, A. M. Stewart. (2020). Sensitivity, reliability and convergent validity of GPS and accelerometers for quantifying peak periods of rugby competition. *PLoS One*, 15 (7): e0236024. https://doi.org/10.1371/journal.pone.0236024

PRESENTATIONS

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DOCTORAL AWARDS

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CHAPTER 1: INTRODUCTION

1.1 Background & Research Problem

The physical preparation of team sport athletes is pivotal to performance. Enhanced physical and physiological qualities improve the likelihood of athletes effectively executing technical skills and tactical roles that may influence match outcome (Mooney et al., 2011). The first step in enhancing the training process is accurately quantifying what the athlete is physically doing (Borresen et al., 2009). Understanding the frequency, intensity, time and type of movements that team sport athletes complete during competition, (i.e. their activity profile) is critical for the design of training that replicates (i.e. is specific to) or exceeds that of matches to adequately prepare athletes for the rigors of competition (Reilly et al., 2009).

Player tracking systems have evolved substantially over the past 30 years, from pen and paper based methods, to the use of video recordings, to more sophisticated wearable electronic tracking devices (Edgecomb et al., 2006), such as Global Positioning Systems (GPS) and inertial sensors. Not only have player tracking systems evolved, but so to have the methods for analysing the data collected by these systems. Global Positioning Systems capture hundreds of movement variables, often ten times per second (10 Hz). Player tracking data analysis has progressed from predominantly reporting absolute movement measures (e.g. total distance - meters) towards relative measures (e.g. relative distance – $m.min^{-1}$) (Aughey, 2011). Relative measures give an indication of the intensity of movement performed, whilst absolute measures indicate the total volume of movement completed. Because relative measures signify the physical output of a player relative to the time they spent on the field, they allow for fair comparison of the movement intensity between whole-match and substitution players, as well as comparison between football codes that have different match durations (Aughey, 2011). Relative measures represent an average movement intensity over a given period of a training session or match (e.g. drill, quarter, half, rotation etc.) and are often used by coaches to prescribe training intensity that replicates that of competition during game-based training such as small-sided games (Farrow et al., 2008). However, if training is prescribed relative to the average intensity of a match, players will likely be under-prepared for the most intense or peak periods of competition (Delaney et al., 2016d).

Team sports are characterised by low-intensity activity interspersed with frequent bouts of high-intensity activity (Aughey, 2010; Deutsch et al., 2007). Despite the majority of team sport competition being spent at submaximal intensity, high-intensity activities are often aligned with key events that determine match outcome (Faude et al., 2012; Gabbett et al., 2016), signifying the importance of physically conditioning athletes for these intense periods of match-play. The most intense periods of a match do not often fall completely within a pre-defined period of time (e.g. 0-5, 5-10, 10-15 minutes etc.) and therefore these analysis methods may underestimate the most intense periods of match-play and overestimate subsequent periods of activity (Varley et al., 2012a). To solve this problem, practitioners and researchers were recommended to use rolling epoch analysis (i.e. epochs from every sampled time point: 0.0 -5.0, 0.1 - 5.1, 0.2 - 5.2 minutes etc.) when attempting to quantify duration-specific peak intensities of competition (Delaney et al., 2015; Varley et al., 2012a).

Duration- and position-specific player movement differences have been observed during the most intense periods of match-play across various football codes including: rugby league (Delaney et al., 2015), rugby union (Delaney et al., 2016d), Australian

Rules Football (Delaney et al., 2017a) and soccer (Delaney et al., 2017b). These investigations provided valuable insights into the highly intermittent nature of team sport movement and highlighted that rolling time-motion analyses may assist practitioners in the design and prescription of training that is more representative and specific to competition. However, there are still many gaps in scientific knowledge when it comes to quantifying and characterising the peak intensities of team sport competition. For example, the sensitivity, reliability and convergent validity of wearable player tracking systems for quantifying peak intensities of team sport competition is not known, limiting a practitioner's ability to interpret and use such data to inform practice. There is also a scarcity of research using inertial sensor (e.g. accelerometer) technology for quantifying peak periods of team sport competition, which is surprising given the reduced accuracy of GPS for quantifying high-velocity and acceleratory movements that frequently occur in team sports (Boyd et al., 2013; Jennings et al., 2010; Rawstorn et al., 2014). Other poorly understood phenomena that will be examined throughout this thesis include: quantifying activity profiles post peak periods of competition, quantifying peak player intensities over very short durations (<1 minute), quantifying peak movement intensity between match-halves and between levels of competition within the same football code (rugby). Characteristics of the peak intensity periods of rugby competition such as the time of the match they occur, within-season trends and whether time on field influences player peak movement intensity will also harvest innovative findings. Lastly, this thesis will explore power law modelling of the decrement in peak movement intensity as exercise duration increases during professional rugby competition, providing coaches with a simple method for modelling the peak periods of competititon as a function of time.

The use of accelerometer technology to quantify peak movement periods of competition in this series of studies may reveal new insights that could improve training monitoring and prescription practices, alongside the more commonly reported GPS measures. Improved understanding of the reliability, sensitivity and convergent validity of wearable technology measures used to determine peak intensities of competition will assist practitioners interpreting the accuracy and reproducibility of peak movement data, thereby informing subsequent training monitoring and prescription decisions. Further, various statistical analyses will be conducted throughout the series of studies to yield novel insights into factors that may influence and characterise peak intensity periods, providing greater context and understanding of these competition worst-case scenarios.

Identification and quantification of the peak intensity periods of competition and the inevitable decline in intensity during the periods following could inform coaching decisions on team and/or individual player substitutions or rotations during competition, if built into real-time software. Another practical application of such data could be to use the activity profile data collected during and post the peak intensity periods of competition to replicate the ‘work’ and ‘active rest’ period intensities and durations during small-sided games training. The time-motion analyses conducted within this thesis could also be used to evaluate the impact of rule changes (e.g. substitution/rotation number changes) on player peak intensities of competition.

Altogether, accurate quantification and characterisation of the peak intensities of competition allows coaches to better prepare their athletes for the worst-case scenarios of competition. The intensity of training can be referenced against the peak periods of activity during competition to ensure the players are prepared for the rigours of match-play in a position- and duration-specific manner (Delaney et al., 2016d). This practice would theoretically increase the likelihood of players thriving and not just surviving during the peak periods of competition due to a reduced relative intensity for the adapted athlete. Coaches need to expose their athletes to very intense periods of training in a periodised manner using game-based methodologies such as small-sided games to elicit physiological adaptations, reduce injury likelihood and improve athlete readiness to perform when confronted with worst-case scenarios during competition. The aim of this thesis is to provide novel insights to help coaches and sport scientists understand, interpret, monitor and prescribe training that is specific to the peak intensities of competition.

1.2 Purpose of Studies

Chapter 3 – Study 1

Quantifying important differences in athlete movement during collision-based team sports: accelerometers outperform global positioning systems.

Aim: To determine the effectiveness of GPS and accelerometer technologies for detecting differences in measures of maximum mean (peak) movement between positions and halves during professional rugby union match-play using a 600 s rolling average epoch.

Chapter 4 – Study 2

Sensitivity, reliability and convergent validity of GPS and accelerometer measures for quantifying rugby union match-play.

Aim: To determine the utility (i.e. sensitivity, reliability and convergent validity) of wearable global positioning systems (GPS) with an integrated accelerometer for quantifying differences in maximum mean movement (5 s to 600 s) within and between: individuals; playing positions; match halves; and level of competition during rugby union match-play.

Chapter 5 – Study 3

Factors influencing the peak periods of elite and sub-elite rugby union competition

Aim: Quantify and characterise the most intense periods of rugby union competition within and between individuals, examining factors that may influence peak intensities:

- Epoch durations (5 s to 600 s),
- Playing positions (forwards, backs),
- Match-halves (first, second),
- Levels of competition (elite vs sub-elite),
- Within-season trends,
- Influence of time on field,
- Time of the game peak periods occur.

Chapter 6 – Study 4

Rugby union activity profiles post peak periods of competition

Aim: Quantify and characterise rugby union athlete activity profiles immediately post the most intense periods of professional competition.

Chapter 7 – Study 5

Modelling professional rugby peak intensity-duration relationships using power law

Aim: Model the peak intensities of professional rugby competition as a function of time using power law and establish prediction model accuracy.

CHAPTER 2: REVIEW OF LITERATURE

2.1 The Training Process

Physical exercise represents a stress to the human body, challenging the maintenance of a constant internal environment, known as homeostasis (Marieb et al., 2007). Several physiological negative feedback mechanisms attempt to negate the changes away from homeostasis that exercise stress provokes, with the human body's response to stress first described by the General Adaptation Syndrome (GAS) (Selye, 1950).

The GAS theoretical framework divides the human response to stress into three phases: alarm reaction, resistance and exhaustion (see Figure 2.1) (Carlson et al., 2010). The alarm reaction phase represents the body's immediate state of shock to an alarming stress (e.g. exercise). The degree of shock to the body depends on the severity of the stress (e.g. exercise intensity) relative to the individual's level of normal resistance (e.g. physiological capacity). Post the alarm reaction phase, the body enters a resistance phase where it attempts to restore homeostasis and increase the body's previous level of stress resistance or tolerance (Selye, 1956). The body then adapts to the stress and increases physiological capacity above baseline via a process known as supercompensation (see Figure 2.2), primarily so that it is able to cope with that same stress if exposed to it again in the future. However, if a stress exceeds an individual's adaptive capability or if additional stress is imposed before the individual has recovered from the initial stress, the third exhaustion stage may ensue (Selye, 1965). The exhaustion stage is characterised by a reduction in resistance to stress levels below baseline, increasing the likelihood of illness, injury and poor physical performance.

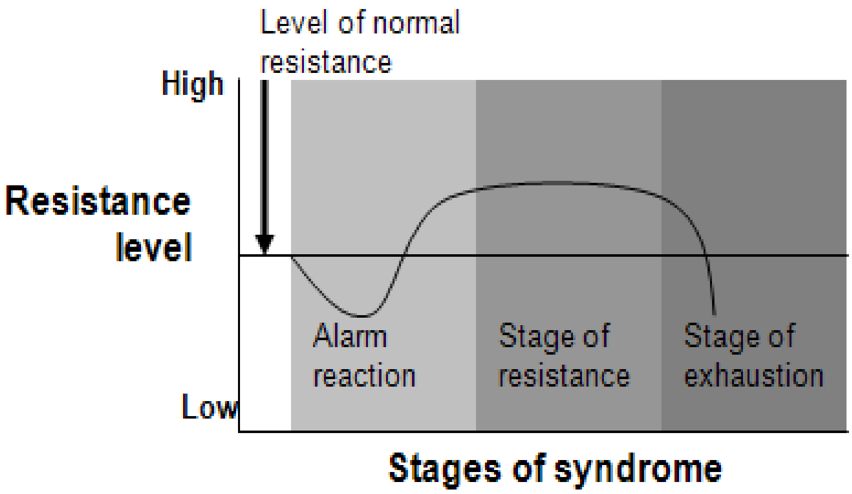

Figure 2.1 The three General Adaptation Syndrome stages. Reproduced from (Carlson et al., 2010).

Physical exercise training can be defined in terms of its process and its outcome (Figure 2.3) (Impellizzeri et al., 2005). The training process is characterised by the systematic repetition and manipulation of physical exercises (Viru et al., 2000). The aim of the training process is to enhance training outcomes such as physical work capability. As exemplified by the GAS and supercompensation models, a balance between training stress and recovery is required to drive supercompensation and positive training outcomes. In order for desired physiological adaptations to occur by a pre-determined time (i.e. day of competition), an individual's training should be systematically sequenced, progressed and applied via discrete training periods, known as training periodisation (Issurin, 2010; Matveyev, 1964).

Training load can be broadly split into two distinct categories: external and internal load (Impellizzeri et al., 2005; Wallace et al., 2014b). External load refers to how much physical work an athlete completed (e.g. distance covered) independent of the athletes internal characteristics (Wallace et al., 2009). Alternatively, internal load refers to the relative physiological and psychological stress imposed on the athlete (Impellizzeri et al., 2005; Viru et al., 2000) (Figure 2.3). For team sport athletes, all training sessions including competitive matches contribute to training load. The first step in enhancing the training process is accurately quantifying what the athlete is physically doing (external load) (Borresen et al., 2009). Objective data on athlete movement during training and competition gives coaches feedback that may inform training design and prescription, to appropriately periodise the training stress to balance fitness and fatigue (Banister, 1991) to adequately prepare athletes for competition. The following sections will introduce the football codes, generalise activity profiles of these team sports, discuss factors that may influence movement and lastly, consider how movement may be measured, analysed and applied.

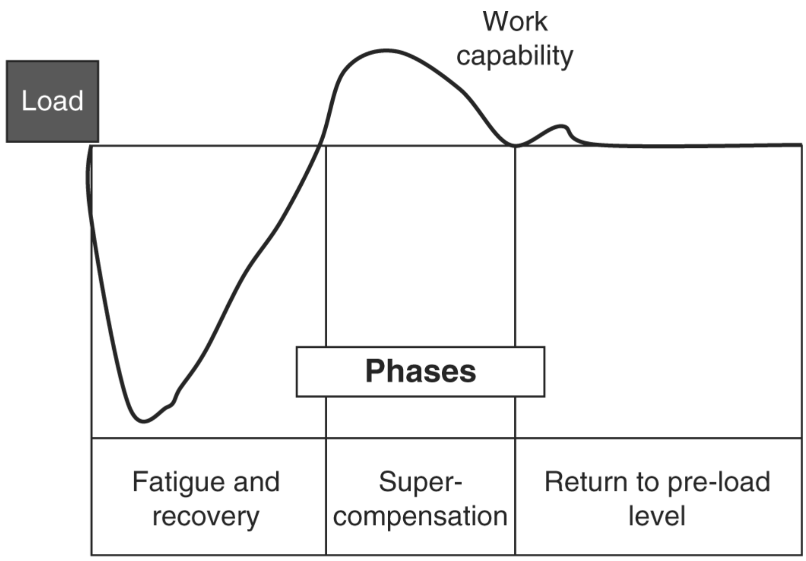

Figure 2.2 The supercompensation cycle, showing the trend of work capability following a single load. Reproduced from (Issurin, 2010), original works from: (Yakovlev, 1955).

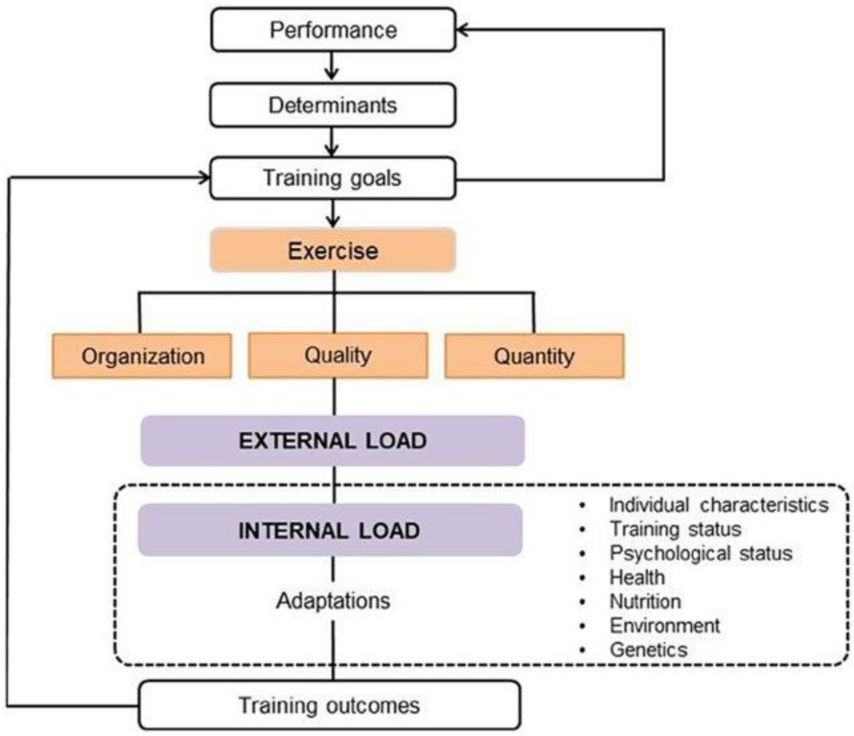

Figure 2.3 Theoretical framework of the training process. Reproduced from: (Impellizzeri et al., 2019), adapted from original author model: (Impellizzeri et al., 2005).

2.2 Team Sport – Football Codes

Football codes including: soccer, rugby, rugby league, Australian Rules Football (AFL), Gaelic Football and American Football (NFL) have large participation rates, stadia crowd attendances, video and audio broadcasting viewers/listeners and revenue. An audience of 3.57 billion tuned in to watch at least one minute of the Russia 2018 FIFA World Cup, according to research published by Publicis Media Sport & Entertainment (Clinch, 2018). Astoundingly, these 3.57 billion viewers represented approximately half of the World's 7.7 billion population at the time. The final on July 15, 2018 between France and Croatia drew a global audience of 1.12 billion according to the sport research company's report. At the turn of the century, approximately 250 million people played association football (i.e. soccer) around the globe, hence being touted “The World Game” by many. Whilst not of the same scale, the 2019 Rugby World Cup held in Japan broke national television broadcast records for the most-watched Japanese live event, with over 25 million tuning in to watch the host nations pool group 38-19 victory over Samoa (Menezes, 2019).

Although the other football codes do not have anywhere near the global participation rates or revenue generating capacity that soccer does, they still have immense economic (Leeds et al., 2018), social (Coalter, 2007), political and cultural impact (Markovits et al., 2013). Due to society’s interest in sports and its impact on various aspects of life, it has become big business for professional leagues and teams. With so much at stake, winning is everything in professional sport and a lot of people care about their team’s performance and results for a variety of reasons. Sporting performance on match day can be attributed to a myriad of factors (Polman et al., 2004), with one factor being the physical output of players. It is for this reason that coaches, sport scientists, strength and conditioning coaches, physiotherapists, dietitians, doctors and other allied health professionals work very hard to ensure that football players are physically prepared to perform during the rigors of competition.

The first step in enhancing the training process and physical preparation of athletes is to accurately quantify their movements (Borresen et al., 2009). Accurate quantification of movement facilitates improved understanding of player activity profiles that may guide training planning and prescription. For example, if the movement of athletes during competition is accurately measured, coaches may use this objective information to prescribe training that is more specific and representative of competition. Football movement may be measured using several time-motion analysis (TMA) methods, including optical systems, global positioning systems and local positioning systems, which will be the topic of latter sections.

Table 2.1: Football code characteristics

	Rugby	Rugby League	Australian Rules Football	National Football League	Association Football (Soccer)	Gaelic Football
No. of Fielded Players (Total)	30	26	36	22	22	30
No. Fielded Players (Team)	15	13	18	11	11	15
No. Bench Players	8	4	4	35	5 to 7	15
No. of Substitutions	8	8-12	90 rotations	Unlimited	3	6
Field Shape	Rectangular	Rectangular	Oval	Rectangular	Rectangular	Rectangular
Field Playing Area	7,000 m^2	7,000 m^2	15,000-18,000 m^2	~ 6,400 m^2	8,250 m^2	10,000-13,000 m^2
Player Density	233 m^2	233 m^2	436-516 m^2	291 m^2	375 m^2	333-435 m^2
Match Duration	80 mins	80 mins	100 mins	60 mins	90 mins	60 mins
Match Period Durations	Halves, 40 mins	Halves, 40 mins	Quarters, 25 mins	Quarters, 15 mins	Halves, 45 mins	Halves, 30 mins
Full-Contact Permitted	Yes	Yes	Yes	Yes	No	Yes
Offside Rule (i.e. 10m/line scrimmage)	Yes	Yes	No	Yes	No	No
Handling of ball allowed	Yes	Yes	Yes	Yes	No	Yes
Forward Passes Allowed	No	No	Yes	Yes	Yes	Yes

2.3 Football Activity Profiles

2.3.1 Physical demands or activity profile?

Descriptive football movement research is typically described as measuring the physical 'demands' of competition. However, player tracking systems such as GPS measure the physical output of players, not the 'demands' of competition (Aughey, 2011). There is no way to gauge if a player has actually met the 'demands' of competition, and if they happen to fatigue then the 'demands' of the sport evidently have not been met. It is for these reasons that the term activity profile is more technically correct and should be used to describe time-motion analyses (Aughey, 2011).

2.3.2 Typical activity profile of footballers

Football code activity profiles are characterised by brief bouts of high-intensity running interspersed with longer periods of low-intensity activity (Rampinini et al., 2007a) (Duthie et al., 2003). Figure 2.4 clearly illustrates the chaotic and stochastic nature of team sport movement with running velocity peaks and troughs. Despite the majority of team sport movement being conducted at low velocities (i.e. walking or jogging speeds), the higher intensity activities are often aligned with key events that determine match outcome such as goal scoring (Aughey et al., 2013a; Faude et al., 2012; Gabbett et al., 2016). Straight sprinting was the most frequent action performed immediately prior to goal scoring in professional soccer, occurring in 45% of 360 goal scoring situations (Faude et al., 2012). Similarly in rugby league, approximately 56% of 2083 repeated high-intensity efforts occurred within 5 minutes of either scoring or defending a try during 21 semi-professional matches across 11 teams (Gabbett et al., 2016). Therefore, conditioning football players for the most intense periods of competition is imperative to match outcome and is central to the purpose of this thesis.

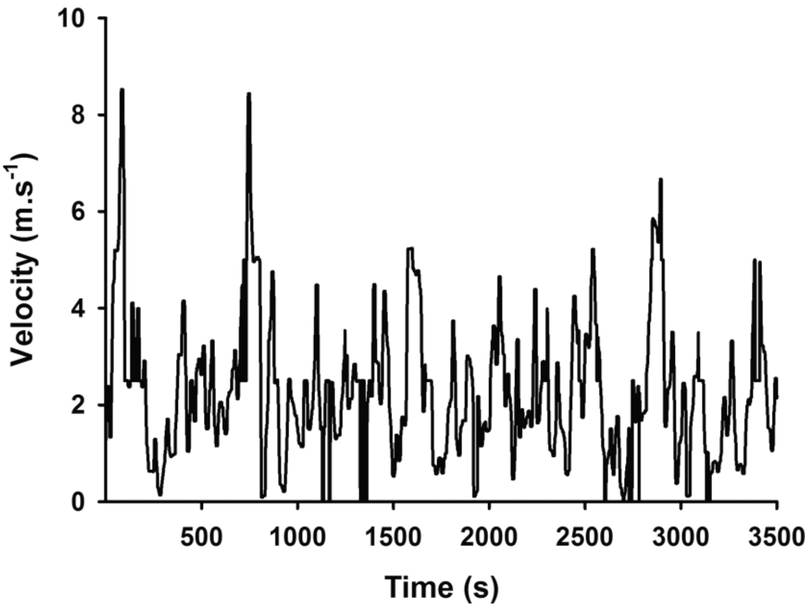

Figure 2.4 Typical GPS velocity trace from a team sport athlete. Reproduced from (Aughey et al., 2013a).

During football competition, high-intensity efforts are often short lived and commence from a low velocity (Figure 2.4). During professional soccer competition, players performed maximal accelerations (> 2.78 m.s^{-2}) eight fold more frequently than sprinting (> 6.94 m.s^{-1} to < 10 m.s^{-1}) (Varley et al., 2013a). In addition, approximately 85% of the maximal accelerations did not exceed the commonly used high-speed running threshold of 4.17 m.s^{-1} (Varley et al., 2013a). Similarly in AFL, unpublished observations using the same speed and acceleration thresholds as the previously mentioned study found that AFL players complete ~ 5 times greater maximal accelerations than sprints (Figure 2.5) (Aughey, 2011). In a study comparing the activity profiles of professional soccer, rugby league and AFL players, repeat sprint bouts were uncommon during competition across all football codes (Varley et al., 2013b). These findings help to debunk the myth and commonly perceived notion that repeated sprint ability is crucial for team sport athletes. Furthermore, the high frequency of maximal accelerations during football competition highlights the importance of developing athlete's acceleratory abilities, and demonstrate that low speed acceleratory movements are still high-intensity in nature given their known high metabolic cost (Osgnach et al., 2010). Exclusion of acceleratory movements that occur at low speeds from analyses would consequently underestimate high-intensity activity of football athletes (Varley, 2013).

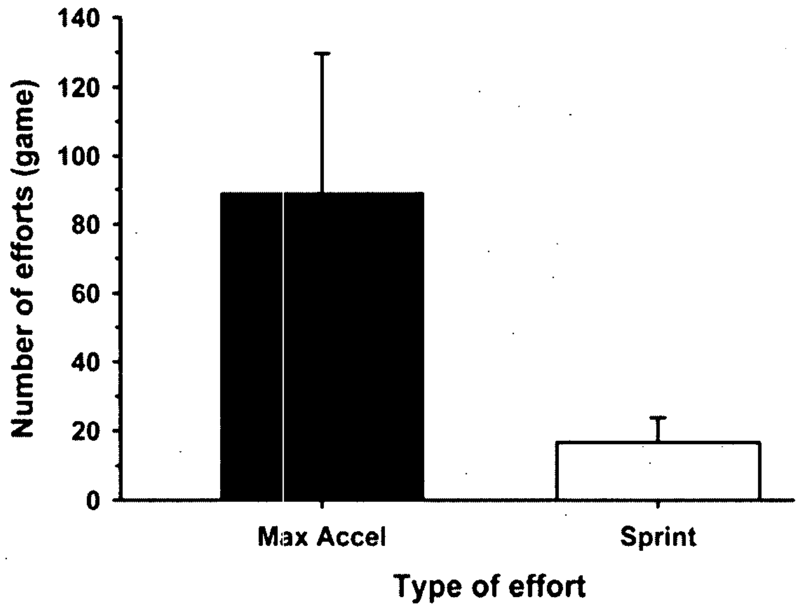

Figure 2.5 The average number of maximal accelerations and sprint efforts per match (mean ± SD) in elite Australian footballers. Acceleration data relate to 2.78 to 10 $m.s^{-2}$ and for sprints > 6.94 $m.s^{-1}$. Reproduced from (Aughey, 2011).

The locomotor profile of football athletes is largely dependent on the frequency and severity of contacts, collisions and tackles. For example, running load decreases in small-sided games that permit contact compared to non-contact games (Gabbett et al., 2012a). Further, an inverse relationship between the number of contact efforts completed and high-speed running distances has been observed during game-based rugby league activities (Johnston et al., 2015a).

The nature of two or more human bodies colliding at high velocities frequently exposes players to muscle damage and increased injury likelihood (Hendricks et al., 2010). Tackles were the most common contact event during professional rugby competition, with an average of 221 tackles per match (Fuller et al., 2007). It is of no surprise then that tackle-related injuries account for up to 61% of all player injuries during rugby competition (Hendricks et al., 2010). Physical collisions cause muscle damage that may contribute to reduced player movement thereafter, with correlations reported between rugby tackle count and both peak myoglobin and creatine kinase activity (Takarada, 2003). Given this, practitioners must accurately quantify the frequency and magnitude of tackles and other collision-based events if they want to be able to adequately contextualise the activity profile of football players. Automatic rugby tackle detection algorithms applied to wearable accelerometer data have demonstrated criterion validity, being able to consistently identify collisions with negligible false positives and false negatives and recall and precisions ratings of 0.93 and 0.96 respectively (Kelly et al., 2012).

A rugby player's ability to win tackle contests may influence match outcome (Gabbett et al., 2009). To evade or engage in tackling an opponent, players must change direction rapidly via deceleration and acceleration (Varley et al., 2013b). Completing frequent changes of direction to avoid opponents limits the ability of players to reach high running velocities, emphasising the importance of developing the acceleratory capacity of footballers. Altogether, collision-based events have a substantial impact on football activity profiles, injury risk and match outcome and should be quantified accordingly to aid subsequent recovery and training prescription practices.

During the opening keynote of the inaugural World Congress of Science and Football (Liverpool, 1987), similarities were drawn between the football codes and common research areas, one being the activity profile of players (Douge, 1988). The speaker stressed that specific components of each football code were interrelated and encouraged knowledge transfer between codes (Douge, 1988). Whilst there are indeed several similarities between the football codes (e.g. invasion sports that are played with a ball, intermittent in nature, on a natural/artificial grass field), a plethora of factors (Table 2.2) may influence football activity profile differences between the codes and is the topic of the following section. Chapter 5 will explore some factors that may influence peak movement intensities of rugby competition.

2.4 Factors Influencing Football Activity Profiles

The nature of football movement is very complex and relates to a host of factors. Factors that may influence football movement have been broadly classified into: situational factors, match-related factors and individual player characteristics (Kempton et al., 2015a). Situational factors relate to things such as opposition strength (Gabbett, 2013) and between match recovery time (Murray et al., 2014). Match-related factors that may influence movement include but are not limited to; possession status (Gronow et al., 2014) match scoreline (Sullivan et al., 2014), playing formation (Bradley et al., 2011), field position and phase of play (Gabbett et al., 2014) and team success (Hulin et al., 2015b). Other frameworks have proposed that fatigue (physical and mental), pacing strategies, contextual and tactical factors are the most influential determinants of athlete movement during football competition (Paul et al., 2015). Physical fatigue, contextual and tactical factors have gained the most attention in the literature, whilst other factors such as environmental factors remain poorly understood (Paul et al., 2015). Too often time-motion analysis research uses a reductionist approach, examining football movement in isolation thereby failing to examine factors that influenced the resultant movement. For these reasons, Table 2.2 provides a simple framework for conceptualising the numerous factors that may influence the intermittent and chaotic nature of football movement. Four clear factor categories emerged from the literature search: 1. Sport-, 2. Team- & Match-, 3. Individual- and 4. Environmental-related factors. The host of factors summarised in Table 2.2 are important to consider when assessing player movement and comparing activity profiles within and between the football codes. Any factors that may influence player activity profiles during competition should be considered when assessing physical "performance" and designing subsequent recovery, training monitoring and prescription practices. It is beyond the scope of this thesis to elaborate on every factor listed in Table 2 that may influence team sport movement, yet the most relevant will be discussed in the coming sections.

2.4.1 Sport-Related Factors

Sport factors relate to code and competition specific structural features, technical requirements, rules, and regulations that may influence athletic movement. For example, the rugby codes, AFL and NFL all are collision-based codes, meaning these sports allow upper body tackling, grappling and bumping within the confines of the rules (e.g. no head high contact). Soccer in comparison, is principally a non-collision sport and does not permit the handling of the ball with the exception of the goalkeeper. Rugby, rugby league and AFL all permit the movement of the ball by hands and feet, however in the rugby codes players cannot pass the ball forwards by hand, whereas AFL players can. A rugby player who receives a forward pass is said to be in an 'offside' position. The player is subsequently penalised for being in an offside position, with a scrum awarded at the location of infringement. Offside rules prohibit players from gaining an unfair advantage by being in front of the ball, increasing their likelihood of scoring a try. Different offside rules and interpretations exist between the football codes, with video assistant referees playing a key adjudicating role in offside decisions (Carlos et al., 2019). The video assistant referees assist the on-field and touch-line referees to minimise officiating errors (Oudejans et al., 2000). Offside rules force receiving players to try and 'time their runs' perfectly by accelerating rapidly and/or attaining high running speed when the ball is being passed to them whilst still being in an 'onside' position to gain a competitive advantage.

Player density is a sport-related factor that has a great impact on football movement dynamics (Wallace et al., 2014a). Player density refers to the total playing surface area divided by the total number of players on the field and is a measure of player congestion. The higher the player density, the less area there is for a player to move until they encounter another player. All football codes have rectangular field shapes with the exception of AFL, played on an oval shaped field. Although AFL has a greater number of players on the field at any one time (36), it has the lowest player density of 417-500 m^2. This allows for a more open style of game where players can express higher running speeds before they typically encounter opposition. In a study comparing the activity profiles or professional soccer (SOC), rugby league (RL) and AFL matches, AFL players covered greater distances relative to time on field (129 ± 17 $m.min^{-1}$) compared to RL (97 ± 16 $m.min^{-1}$) and SOC (104 ± 10 $m.min^{-1}$) (effect size [ES]; 1.0-2.8) (Varley et al., 2013b). In contrast, rugby league and rugby have much smaller rectangular field playing areas of ~ 7000 m^2 and have player densities of ~ 269 m^2 (26 players) and ~ 233 m^2 (30 players) respectively (Table 2.1). Increased player density promotes player contact, change of direction, acceleration and deceleration events whilst limiting high-speed movement (Gaudino et al., 2014; Halouani et al., 2014). Football teams alter playing formations and tactics during competition, congesting space with more players as a defensive strategy or leaving open field areas free of players to aid offensive pursuits and thereby dynamically altering player density in given areas of the field (Wallace et al., 2014a).

Small-sided games (SSG) are often incorporated into football code training, altering playing area and number of players (thus player density) alongside drill rules and coach feedback to purposefully modify the skill and activity profile focus of the drill (Farrow et al., 2008). Small-sided games provide coaches with an effective training methodology that develops player's physiological, tactical and technical skills abilities concurrently in game-specific environments (Gamble, 2004; Hill-Haas et al., 2011; Rampinini et al., 2007b). The ability to manipulate several factors during SSG training drills (e.g. player density, playing rules etc.) as opposed to matches where coach control is limited, has allowed insights into the effects of these factors on player activity profiles and physiological responses. For example, increased player density during SSG's resulted in an increase in the total number of agility manoeuvres for elite AFL athletes (Davies et al., 2013). During rugby league training, incorporating wrestling into SSG's decreased player distances covered across all running velocities, whilst increasing the number of mild, moderate and maximal accelerations and repeated high-intensity effort bouts (Gabbett et al., 2012a). Increasing SSG pitch area and decreasing player numbers subsequently increases player heart rate (HR), ratings of perceived exertion (RPE) and blood lactate concentrations (Rampinini et al., 2007b; Sampaio et al., 2007).

The duration of the exercise bout alters team sport player activity profiles and pacing strategies (Delaney et al., 2016c; Sampson et al., 2015; Waldron et al., 2014). As football match duration increases there is a decay in total distances covered across progressive segments of rugby (Lacome et al., 2013; Roberts et al., 2008), rugby league (Sykes et al., 2011; Waldron et al., 2013) and AFL matches (Aughey, 2010; Wisbey et al., 2010). Self-regulated progressive declines in movement intensity across a match is indicative of athletes pacing their efforts in an attempt to distribute energy resources to optimise running performance, limiting eventual reductions in movement compared with baseline values, known as fatigue (Waldron et al., 2014). Whole-match football players generally adopt a 'slow-positive' pacing profile, characterised by gradual declines in total and high-intensity running, while part-match substitution players tend to adopt 'all-out' higher-intensity bouts reflective of their shorter duration on field (Waldron et al., 2014).

Fundamental activity profile differences exist within football codes due to player positions (Duthie et al., 2005; Gabbett et al., 2012b; Reilly, 1976; Wisbey et al., 2008). Different playing positions across all the football codes have specific technical and tactical roles that aim to help the team achieve success. Specific positional roles often require players to have particular body shapes, sizes, compositions (Kraemer et al., 2005), physiological capacities (Duthie et al., 2003; Mooney et al., 2011), psychological temperaments (Cox et al., 1995) and technical skills (Woods et al., 2018). In the football codes, players in positions that frequently engage in collision-based movements to win or protect possession of the ball (e.g. NFL defensive lineman, rugby forwards) are typically physically bigger, taller, stronger and have a greater body fat percentage than those who perform those movements less frequently (Duthie et al., 2003). In contrast, player's whose positional role is to evade collision-based events in an attempt to run past opposition to score try's, touchdowns or goals are generally physically smaller, with lower body fat and higher muscle mass percentage, thereby improving power to weight ratio and acceleratory capabilities (Duthie et al., 2003) (i.e. Isaac Newton's second law of motion: Force = Mass × Acceleration, or Acceleration = Force / Mass) (Newton, 1687). The physical, physiological, technical, tactical and psychological differences between positions illustrates the importance of training football athletes in a position specific manner and assessing activity profiles relative to role.

The amount of time the ball is in play has a substantial impact on football activity profiles (Delaney et al., 2016c; Gabbett, 2015; Wallace et al., 2014a). An investigation examining the evolution of soccer World Cup finals structure, speed and patterns from 1966 to 2010 found that the duration the ball was in play decreased substantially, whilst stoppage duration increased, influencing work: rest ratios (Wallace et al., 2014a). The increased rest periods between ball in play bouts likely contributed to the 15% increase in ball (game) speed across the 44 year period, allowing greater player recovery and subsequently more intense play (Wallace et al., 2014a). During 22 semi-professional rugby league matches coded for activity and recovery cycles, the average match duration was 84.5 ± 3 minutes compared to 47.9 ± 4.1 minutes of time when the ball was in play (Gabbett, 2015). Put another way, the ball was in play on average 56.7% of the time during rugby league matches. Results illustrated greater movement, contact and repeated high-intensity effort (RHIE) intensity when movement data were expressed relative to ball-in-play time and that movement intensity declines during longer passages of play (Gabbett, 2015). Somewhat surprisingly, The Wall Street Journal in 2010 reported that there is only 11 minutes of ball-in-play time during NFL American Football matches (Biderman, 2010). During the English Premier League 2017-2018 season the ball-in-play time averaged across the 20 teams in the competition was 56 minutes, representing 62% of the 90 minute matches (talkSPORT, 2017). Altogether, ball-in-play time across the football codes varies considerably and reflects exercise duration, which has profound effects on player exercise intensity, pacing strategies and fatigue.

2.4.2 Team and Match Factors

A host of factors prior to and within competitive matches influence the way individuals and teams move. These factors range from team tactics, formations and patterns of play to the stage and position a match is in at any given time (Table 2.2). In fact, match difficulty indices have been created to manipulate training loads with the aim of prioritising athlete readiness for the matches of greatest perceived importance (Kelly et al., 2007; Robertson et al., 2014), inevitably influencing subsequent match activity profiles. One model used the quality of opposition, the number of days between games and match location to help coaches predict match difficulty and thereby help them to plan and monitor training loads during competitive phases of the season (Kelly et al., 2007). Another match difficulty index designed specifically for Super Rugby was created based on the influence of five external factors on previous match outcome, including: match location, days break between matches, time-zone change and opposition ladder position (both current and previous year) (Robertson et al., 2014). The three cross-validated Super Rugby match difficulty indices that were constructed displayed match outcome classification performances of 63.7-66.2%, meaning they may be used to predict match difficulty and to inform training load periodization. Modifying training loads prior to competitive matches will inevitably alter player and team fitness and fatigue and thereby influence player activity profiles during competition.

Stark match activity profile differences have been observed between more and less successful football teams across the football codes (Di Salvo et al., 2009; Hulin et al., 2015b; Rampinini et al., 2009). During Italian Serie A professional soccer competition, players from less successful teams covered 11% more high-intensity running (> 14 km.h^{-1}) and 9% more very high-intensity running distance (> 19 km.h^{-1}) than their more successful team counterparts (Rampinini et al., 2009). Similarly, during English Premier League (EPL) competition, lower ranked soccer teams completed more high-speed activity then their higher ranked counterparts (917 ± 128 m vs. 885 ± 113 m, p = 0.003) (Di Salvo et al., 2009). It was proposed that this may have been a direct consequence of lower ranked teams attempts to regain the ball with an inability to retain possession of the ball. During elite rugby league match play, a greater number of collisions during competition was related to a greater rate of success (winning), however increased high-intensity and total distance running were not related to success during elite competition (Hulin et al., 2015b). For instance, compared with the hit-up forwards of the 'high-success' team, 'low-success' hit-up forwards covered greater total (ES = 0.7 to 1.7 ± 0.4 to 0.5) and high-intensity running distances (ES = 0.9 to 1.5 ± 0.8 to 1.1) and were involved in fewer collisions (ES = 0.6 to 0.7 ± 0.3 to 0.5) during several 5-minute match periods. Similarly, during the peak and mean periods of match-play, sub-elite rugby league forwards from successful teams covered less total (p = 0.02; p = 0.01) and high-intensity running distances (p = 0.01; p = 0.01), yet were involved in a greater number of collisions than those forwards from less successful teams (p = 0.03; p = 0.01) (Hulin et al., 2015a). Results across the football codes indicate that greater total and high-speed distances covered do not necessarily relate to success (winning).

Ball possession status influences footballer activity profiles and team success (Bradley et al., 2013a; Gronow et al., 2014; Rampinini et al., 2009). During professional AFL competition, teams that had a greater amount of ball possession and time spent running > 14 $km.h^{-1}$ without possession were significantly more likely to win match quarters (Gronow et al., 2014), although time in possession was not significantly different in wins vs losses. Despite high-intensity running discrepancy between teams, those players from more successful teams covered 18% greater total distance whilst in possession of the ball compared to less successful teams. When in possession of the ball the better teams completed 16% more high-intensity running (> 14 $km.h^{-1}$) and 14% greater very high-intensity running (>19$km.h^{-1}$) (Rampinini et al., 2009). Similar findings were apparent during EPL competition, with teams that hold greater ball possession (55 ± 4%) also completing 31% more high-speed running distance (m) when in possession and 22% less without ball possession than in teams with lower ball possession percentages (46 ± 4%) (Bradley et al., 2013a). In contrast, during professional rugby league match-play, defensive play without possession of the ball increased physical output of players, with distance covered and frequency of both collisions and repeated high-intensity efforts compared to when in possession attacking (ES: 0.62-1.41) (Gabbett et al., 2014). It is clear that ball possession status influences the activity profiles of professional footballers and is associated with match outcome.

The match score during competitive football influences player and team activity profiles (Murray et al., 2015; Redwood-Brown et al., 2012; Sullivan et al., 2014). During AFL competition small score margins were associated with increased physical activity and decreased skill efficiency (Sullivan et al., 2014). Intensity indicators of total and high-speed (>14.5 $km.h^{-1}$) running distance per minute and bodyload per minute (GPS and accelerometer derived measures) all increased ($p < 0.05$) when the match score was close (Sullivan et al., 2014). Similarly, during international rugby sevens competition, close halftime score lines were associated with increased high-speed running distances (Murray et al., 2015). However, professional soccer forwards spent a greater percentage of match time running at > 14.4 km^{-1} when leading their opposition, whilst defenders spent more time running above 14.4 km^{-1} when trailing their opposition (Redwood-Brown et al., 2012). Altogether, findings illustrate that footballers alter their activity profile depending upon match score line, however more research is required to determine the magnitude of alteration using standardised TMA methods across the codes.

A plethora of other team and match related factors may influence player and team activity profiles during football competition, yet discussing them all was outside the scope of this literature review so will be mentioned in brief. Dynamics of team-team and player-team movement synchrony (Duarte et al., 2013; Gonçalves et al., 2017), field position and phase of play (Gabbett et al., 2014), home vs. away matches (Aquino et al., 2017) and travel (Lo et al., 2019) are some other team and match related factors that may influence football player activity profiles.

2.4.3 Individual Factors

An individual's physical, cognitive, tactical and technical prowess may influence how they move during football competition. Many of these factors are within the individual's control to some degree (e.g. nutrition, hydration, sleep practices), whereas others are not, (e.g. coach instructions on playing role, time allocated on field or physical height). Whether controllable or not, numerous factors relating to each individual footballer influence the way they, their teammates and their opposition move (Table 2.2). Several factors that may influence the peak intensities of professional rugby competition are investigated in Chapter 5.

The physical capacity and qualities of footballers influences their activity profile during competition (Duthie et al., 2017; Mooney et al., 2013; Mooney et al., 2011). Australian Rules Footballers who scored greater on the YoYo intermittent running level 2 test covered greater distances running above 15 $km.h^{-1}$ and exhibited lower declines in running distances below 15 $km.h^{-1}$ across the course of a match (Mooney et al., 2011). Rugby league players' running intensity during competition is underpinned by their individual physiological qualities, with players demonstrating greater maximal speeds during physical testing able to maintain higher running intensities over short durations whilst exhibiting sharper declines in running intensity as duration increased (Duthie et al., 2017). Professional rugby player sprint performance times over 10, 20 and 30 m had moderate to small negative correlations with line breaks (*r* = ~ 0.26), meters gained (~ 0.22), tackle breaks (~ 0.16) and tries scored (~ 0.15) during competition (Smart et al., 2014). Rugby front row forwards (i.e. props and hookers) are exposed to higher impact forces during scrums compared to other forwards, necessitating greater strength. Forces achieved during scrummaging for props (1420 ± 320 N) and locks (1450 ± 270 N) is greater when compared with loose forwards (1270 ± 240 N) (L. Quarrie et al., 2000). During soccer, player's maximal oxygen uptake ($\dot{V}O_2max$) is correlated with distance covered, level of work intensity, sprint number and ball involvements (Helgerud et al., 2001). Results across the football codes signify the importance of developing player's physical capacities, with the hope of translating increased physical capacity into increased physical output during competition.

A player's assigned position largely governs their activity profiles during training and competition (Quarrie et al., 2013). Position specific body composition and physical capacity adaptations then inevitably influence subsequent match activity profiles. Footballers are often recruited to play in certain playing positions due to their body anthropometrics, composition and physical capacity (Duthie et al., 2003). For example, physically tall footballers (e.g. 200 cm) are often recruited to positions that engage in aerial contests to either catch/mark or tap the ball to their teammates, such as rucks in AFL, locks in rugby or goalkeepers in soccer. In rugby, half backs (i.e. scrum- and fly-halves) require good speed and acceleratory qualities as they need to frequently accelerate away from approaching defenders (Duthie et al., 2003). Altogether, footballers are often assigned to play in specific positions due to their physical qualities and capacities, influencing subsequent activity profiles and adaptations. This perpetual "chicken or the egg" cycle repeats over time, yielding greater differences in player's physical capacities between positional groups due to exercise specific adaptations.

The duration of an exercise bout influences an individual's selected exercise intensity during team sport (Gabbett et al., 2015; Waldron et al., 2014). Whether a footballer is a 'starter' (potential whole-match player) or 'substitute' (part-match player) alters the exercise bout duration and pacing profile of an individual. In an attempt to optimize running performance whilst not doing more than necessary, team sport whole-match players generally adopt a 'slow-positive' pacing profile that is characterised by gradual reductions in total and high-intensity running as exercise duration increases (Waldron et al., 2014). In contrast, their part-match (i.e. substitute) counterparts tend to select an 'all-out' (i.e. very high intensity from the start of a bout) or 'reserve' (i.e. reserve energy via decreased running distances as the number of team interchanges diminishes) strategy depending on their playing role (Waldron et al., 2014). The number of players on the bench and substitutions/rotations allowed varies widely across football codes from 3 in soccer, 90 in AFL (2019) and unlimited in NFL (Table 2.1). Stark substitution rule differences between football codes heavily influences exercise bout duration, pacing strategies and therefore activity profiles of individual's during competition. The duration of exercise bouts within and across separate periods (e.g. quarters or halves) of matches is a key consideration for practitioners to inform real time substitution decisions and subsequent recovery and training practices.

2.4.4 Environmental Factors

Several environmental factors such as heat, humidity, hypoxia (altitude), air pollution and playing surface influence team sport activity profiles (Table 2.2). Different environmental conditions change the physiology of human beings during exercise, thereby influencing the way humans respond acutely and adapt chronically to exercise. It is beyond the scope of this review to discuss the physiological mechanisms, responses and adaptations to these environmental conditions, so please see literature on: heat (Hargreaves et al., 1998; Tyler et al., 2016), humidity (Maughan et al., 2012), hypoxia (Bailey et al., 1997; Böning, 1997; Inness, 2017), air pollution (Rundell, 2012) and playing surface conditions (Fleming, 2011; Heidt JR et al., 1996). The influence of heat and hypoxia on team sport activity profiles are the most commonly reported in the literature, so will be the topic of the following sections.

During professional AFL competition played in hot conditions (mean ± SD: 27 ± 2° C) compared to cooler conditions (17 ± 4° C), player's modulated their activity profile by reducing running distances covered at lower intensities to preserve their ability to perform high-intensity activities (Aughey et al., 2014). Reduced physical output of team sport athletes in hot conditions is likely due to alterations in energy metabolism, cardiovascular function, fluid balance and central nervous system function/motor drive to aid thermoregulation (Hargreaves et al., 1998).

At altitude where the partial pressure of oxygen is reduced, the activity profile of soccer players is reduced even at moderate (1600 m) altitude when compared to sea level (Garvican et al., 2014). The peak 5 minutes of total distance and high-velocity running > 4.17 $m.s^{-1}$ covered during soccer competition was reduced at 1600 m when compared to sea level. In addition, the decline in soccer players total distance, high-velocity running and maximal accelerations (> 2.78 $m.s^{-2}$) post the peak 5 minute period of match-play was greater at altitude when compared to sea level (Garvican et al., 2014). Studies conducted at even higher altitudes (i.e. 3600 m) have similarly reported that running distances covered during competitive soccer matches are reduced for both sea level and high-altitude youth natives, with acclimatization not able to protect against the deleterious effects of altitude (Aughey et al., 2013b).

Coaches and sport scientists need to be aware of environmental conditions when preparing or acclimatizing team sport athletes to compete in certain environments. Practitioners also need to be cognisant of ways to counteract the deleterious effects of various environmental conditions to aid sporting performance via strategies such as: precooling, hydration, clothing/footwear considerations, pre-, in- and post-match nutrition. Improved understanding of the many environmental factors that may influence team sport activity aids interpretation of training and match movement data. Subsequent athlete recovery and training prescription should reflect both the environmental and exercise stress.

Findings from this review of the literature across the football codes underpins the importance of considering several factors when analysing and interpreting the activity profiles of team sport athletes. Four clear factor categories emerged from our literature review: 1. Sport-, 2. Team- & Match-, 3. Individual- and 4. Environmental-related factors. It is hoped that the presented framework illustrated in Table 2.2 aids researchers in designing future projects with multivariate mixed-models that incorporate some of these factors into their analyses to help explain the complexity of team sport movement. The framework presented may also help practitioners to contextualise player and positional activity profiles, aiding interpretation and application of the data for training monitoring and prescription.

Table 2.2 Factors that may influence team sport activity profiles

Sport Factors	Team & Match Factors	Individual Factors	Environmental Factors
Technical requirements	Team tactics	Physical characteristics/fitness	Temperature
Player density (playing area/no. players)	Team player formations	Fatigue	Humidity
Substitutions or Rotations	Team player selections	Body size & composition	Altitude
Match duration	Team organisation/behaviour	Movement efficiency	Air pollution
Match period duration (halves, quarters)	Team cohesion	Playing position	Field surface
Match period intermission duration	Opposition movement	Coach instruction on playing role	Rain
Stoppage time	Level of opposition	Time on field (e.g. starter vs sub)	Wind
Playing positional roles	Time ball in/out of possession	Pacing strategy	Light
Phase of the season	Time ball in vs out of play	Motivation	
Microcycle recovery length	Stage of match	Experience	
Travel requirements	Match scoreline	Vision/scanning ability	
General movement rules	Field position of play	Decision making	
Physical contact rules	Phase of play	Movement preparation (warm up)	
Offside rules (e.g. 10m rule)	Yellow/Red Cards	Sleep	
Designated movement area rules	Home vs away match	Nutrition	
Forward passing rule	Match travel requirements	Hydration	
Disciplinary rules (e.g. cards, sin bin)		Injury	
Several sport specific rules		Illness	

2.5 Quantifying Football Activity Profiles

2.5.1 Global Positioning Systems

Nobel Prize winning discoveries in physics, numerous engineering feats, an aeroplane tragedy leading to political policy change and commercialisation of sport amongst other events have paved the way for satellite-based radionavigation systems we use today to measure human locomotion. The development of the GPS technology by the United States Department of Defence in 1973 and first satellite launch in 1978 (Lachow, 1995) was only possible due to the seminal work of 1944 Nobel laureate in physics, Isidor Rabi alongside many predecessors, namely Sir Isaac Newton and Albert Einstein. Rabi and his students invented the magnetic resonance method through their precise measures on the hydrogen atom (Rabi et al., 1938). Prior to their novel invention, the creation of the precise timepiece that is the foundation of satellite navigation; the atomic clock, was not possible. The atomic clock enabled the exact and stable calculation of the length of time it takes a radio signal to travel from a satellite in space to a receiver on earth, allowing distance to be derived by multiplying the transit time by the speed of light (i.e. 299,792,458m.s^{-1}) (Aughey, 2011). The initial idea of using atomic transitions as very stable frequency references to measure time is attributed to Lord Kelvin via his 1867 collaboration with Peter Guthrie Tait, 'Treatise on natural philosophy' (Kelvin et al., 1867). Further, without knowledge of Albert Einstein's theories of general and special relativity (Einstein, 2003), we would be ignorant to the fact that both speed of motion and gravity alter time, yet the speed of light remains constant. The consequence of relativity being that small errors between the measurements of time on earth compared to space (i.e. 38 microseconds per day) leads to big errors in position, speed and distance estimates on earth. The satellites travel at an orbital speed around the earth of approximately 14,000 km.h^{-1} and due to their speed the space based atomic clocks fall behind earth-based receiver time by 7 microseconds per day (special relativity). The theory of general relativity states that gravity alters time, with clocks in space with lower gravity running faster than those on earth. Hence satellite-based clocks orbiting earth approximately 20,000 km away run 45 microseconds per day faster than earth-based clocks. Current radionavigation satellite atomic clock installations account for combined effects of both special and general relativity by factoring the 38 microseconds difference into calculations of distance to more accurately measure position and speed of earth-based receivers.

The Global Positioning System (GPS) is a satellite-based navigation technology, initially developed by the United States Department of Defence for military practices (Lachow, 1995). Civilian use of GPS technology was only permitted after a civilian airplane carrying 269 people was shot down by Soviet jet interceptors when accidentally straying into Soviet prohibited airspace in 1983 (Enge et al., 1999). Following the tragedy, President Ronald Reagan declared the United States would make GPS freely available for civilian use through the Department of Transportation (Lachow, 1995), as access to a better navigational system may have prevented the tragic loss of life. However, in order to balance civil benefits and military risks, the Department of Defence introduced an intentional error code to the civilian satellite transmission named Selective Availability (Lachow, 1995). The signal degradation was engineered to limit hostile forces using the system with lethal precision. Differential GPS was developed to circumvent the errors associated with Selective Availability. Differential GPS utilises a stationary receiver in addition to a roving GPS receiver. The fixed and calculated location of the differential GPS receiver is then compared with that given by the satellite, establishing signal error. Signal corrections can subsequently be sent and applied to the roving GPS receiver, substantially enhancing its positional accuracy (Townshend et al., 2008).

The GPS constellation originally operated via 24 satellites that orbited the earth (Townshend et al., 2008), with 31 satellites functional in 2019. There are four Global Navigation Satellite Systems (i.e. GPS-USA, GLONASS-Russia, Galileo-Europe and BeiDou-China), with approximately 110-120 satellites currently orbiting earth (Li et al., 2015). If a minimum of four satellites are in communication with a earth-based receiver, an accurate position of the receiver can be triangulated via spherical trigonometry (Larsson, 2003). Obtaining this minimum number of satellites should not be an issue as 24 total satellites give 24 hour global coverage with 4 satellites travelling 6 different orbiting paths (hence the extra number of satellites in each constellation in case of occasional signal drop out). Utilising a complex algorithm, the navigation systems are also able to calculate the speed of displacement (speed) by measuring the rate of change in the satellites' signal frequency (Doppler shift) produced through movement of the earth-based receiver relative to the satellite (Larsson, 2003; Schutz et al., 1997). Consequently, the earth-based receiver is able to calculate and record data on position, distance, time and velocity (Larsson, 2003), which is of interest to sports coaches and scientists if used to track human movement.

The first application of GPS technology for athlete tracking purposes was in 1997. One subject was equipped with a commercially available GPS receiver (GPS 45, Garmin, Lenexa, KS 66125, USA) while walking, running and cycling at various velocities (76 tests) to compare GPS receiver accuracy with chronometry (Schutz et al., 1997). There was a significant relationship (r = 0.99, p <0.0001) reported between the speed of displacement assessed by GPS compared to that measured by chronometry for walking and running (2-20 km.h^{-1}) and cycling (20-40 km.h^{-1}). While promising, the use of a swiss chronometer and metronome to pace efforts was hardly a gold-standard verification of the validity of GPS for measuring velocity (Aughey, 2011). Although differential GPS greatly improved signal accuracy, the receivers needed to be made considerably lighter (initially weighing approximately 4 kg) to be a viable method of athlete tracking (Terrier et al., 2001). Similarly, receivers needed to be engineered to withstand heat, moisture, impact forces and have improved battery life to be feasibly applied in a range of athletic settings (Aughey, 2011).

Selective Availability was turned off in May 2000, allowing civilians to receive a non-degraded signal globally. The applicability of differential GPS was further reduced with the adoption of the Wide Area Augmentation System and European Geostationary Navigation Overlay Service (Witte et al., 2005). These air navigation systems were founded on the same premise as differential GPS correction, only the 'differential' receiver is integrated inside the GPS receiver itself. Non-differential GPS receiver accuracy, integrity and availability were subsequently improved. Coupled with reduced weight, size, cost and ease of use through commercialisation, non-differential GPS provided new opportunities for the measurement of human locomotion in sporting contexts (Townshend et al., 2008).

2.5.2 Global Positioning Systems as a Player Tracking Tool

The first commercially available GPS device specifically designed for quantifying athletic movement was the Sports Performance Indicator (SPI 10), developed by GPSports Systems (Edgecomb et al., 2006). Since then, there has been a rapid uptake of GPS technology, with the largest commercial retailer Catapult Sports currently used by 2,500 teams across 39 sports as of June 2nd, 2019 (https://www.catapultsports.com/). A Google Scholar search for "global positioning systems" yields 3.5 million article results, with ~ 3.1 million (90%) occurring in the last 30 years between 1990 and 2020.

The prolific adoption of GPS in elite team sports is testament to its perceived worth and impact on player and team preparation and performance. Global Positioning Systems provide objective data that may inform decision-making processes, including but not limited to: training load management (Gallo et al., 2015), training prescription (Delaney et al., 2015), player readiness to play (Barrett et al., 2016), injury risk (Gabbett et al., 2011a), and player interchange decisions (Aughey et al., 2010; Delaney et al., 2016c).

Global Positioning System receivers designed for athletic populations are small, robust, waterproof and lightweight, enabling seamless portability that was not so 20 years ago. Today, GPS receivers are approximately the size of a small mobile phone. For example, Catapult Sports released the OptimEye S5 receiver in 2013 that has a height, width and depth of 96 mm × 52 mm × 14 mm, with its predecessor model weighing only 67 grams, compared to initial GPS models weighing ~ 4 kg. Further miniaturisation is likely into the future with flexible 'second-skin' wearable adhesives akin to postage stamps or temporary tattoos are already on the market that integrate seamlessly with the human body.

When the GPS receiver is turned on, it collects information on player position via communication with satellite networks and subsequently calculate distance and velocity. The receivers are placed within a custom-made vest or pouch, situated between the player's scapulae. Any impairment of the radiofrequency signal between the earth-based receiver and the satellites in space will degrade positional measurement accuracy. Stadia structures such as overhanging roofs and tall surrounding buildings may obstruct signals and are common practical issues in sporting contexts held in large stadiums. Whilst there are only four satellites needed to triangulate the position of a GPS receiver on earth, a moderate negative relationship exists between the number of available satellites and total distance measurement error (Gray et al., 2010). It is for this reason that some manufacturers have developed receivers that have antennas for multiple satellite installations, that has both GPS and GLONASS satellite accessibility (i.e. access to 57 orbiting satellites), increasing positional accuracy and reducing the likelihood of signal drop out.

The dilution of precision (DOP, i.e. the position and distribution of satellites in space relative to the earth-based receiver) also influences positional data accuracy (Witte et al., 2005). A more even distribution of satellites orbiting the earth across the horizon that have direct line of sight to the earth-based receiver will lower the DOP and thereby improve position measurement accuracy. For example, a DOP value of 1 indicates the ideal distribution of satellites in the sky, with 1 satellite positioned directly above the earth-based receiver and the remaining satellites evenly distributed across the horizon (Witte et al., 2005). Conversely, if the satellites are tightly clustered above the receiver the DOP value increases, with a maximum value of 50 (Witte et al., 2005). The positional measurement accuracy of GPS systems are reliant on unobstructed satellite communication and geometry with earth-based receivers, thereby also influencing the measurement accuracy of both distance and speed.

Modern GPS devices are able to record, store and retrieve large quantities of data at high-speeds (1-10 Hz) via wireless transmission in real-time, with an approximate 4-6 hour battery life. The movement data of each player within the team that is ‘wearing’ a GPS receiver can then be downloaded to a computer post training or match. The data is then processed and analysed via proprietary or custom-built software, with results reported to key stakeholders such as coaches and players in a timely manner. In fact, player activity profile data can be relayed to coaches in real-time via the use of a receiver connected to a laptop to enact changes to training drills or player feedback instantaneously. Player tracking using GPS is much more time efficient than many previous time-motion analysis techniques such as notational analysis and manual video analysis, as an observer is not required to code events and all players can be tracked simultaneously. Generating timely objective feedback on player activity profiles for key stakeholders is critical, enabling informed decision-making on training planning and prescription as well as having ramifications during competition (e.g. substitution/rotation decisions).

Global Positioning Systems are relatively expensive, although are often more cost effective than vision-based tracking systems, where several high-resolution cameras must be set up at specific locations within stadia. The fixed location of these vision-based systems within stadia is an issue for teams that train on different grounds, meaning they either receive no training data or have to combine data from multiple player tracking solutions, with different measurement error. Further, the vision-based system used in a team's home stadium may be different to opponent's system and thus activity profile comparisons between home and away matches becomes problematic. However, nowadays most vision-based player tracking solutions are implemented via league wide deals. Many vision-based systems incur greater ongoing costs than GPS systems (e.g. service charges for analysis of match data), with the exception of GPS service fees that may be included in the warranty (Varley, 2013). Subsequently vision-based systems are principally used by professional teams and not accessible to sub-elite or amateur teams (Varley, 2013).

Adding to financial and time burden, semi-automated systems require an observer to identify players occluded from the camera view or during adverse environmental conditions (Carling et al., 2008). Video analysis of player movement may take hours to extract variables using some systems that can be reported in real-time comparatively using GPS (Petersen et al., 2009). In addition, some video analysis methods require prior determination of mean speeds of each gait movement pattern to improve distance measurement accuracy, as players are not often perpendicular to the cameras, increasing parallax error (Deutsch et al., 1998; Dobson et al., 2007). In contrast, the only prior testing recommended for GPS use is to place the receivers in an open sky environment 15 minutes prior to use, allowing the receivers to connect to satellites (Duffield et al., 2010), improving ease of use and adoption of the technology. Perhaps it for these reasons that use of portable wearable GPS technology is becoming more common across the globe with team sport organisations.

Global Positioning Systems provide many advantages to vision-based systems but also have many limitations that need acknowledgement. The first inherent limitation of satellite-based systems is that they require unobstructed signal line of sight to satellites (Larsson, 2003). Thus, measurement of player position in indoor environments or in stadiums that close their retractable roof due to wet weather is not possible. Positional accuracy of GPS are also influenced by the number of satellites “locked on” to the receiver, satellite or receiver clock error, DOP, atmospheric effects, obtrusive infrastructure, sampling frequency, chipset quality, radio frequency interference, antenna selection and orientation to help account for multipath error (Townsend et al., 1994) as well as software and data filtering procedures.

A practical limitation of wearable player tracking solutions is that some sporting governing bodies (e.g. National Football League) do not allow the use of electronic performance and tracking systems (EPTS) in matches due to player safety concerns. This was also the case in soccer until the rules of the game were changed by The International Football Association Board in 2015, permitting the use of EPTS technology during competitive matches ("Amendments to the laws of the game," 2015).

These rules have hindered direct comparisons between these football codes team training and match movement data and research into competitive activity profiles.

The use of wearable GPS with integrated sensors to quantify activity profiles of team sport athletes in training and matches is now ubiquitous (Aughey, 2011; Cardinale et al., 2017; Cummins et al., 2013). Technological advancements have improved the efficiency of human movement data collection, processing, analysis and reporting, whilst also increasing data accuracy and reproducibility. All player tracking technologies should undergo rigorous quality assurances, as without valid and reliable tools and measures, any data collected is meaningless (Safrit et al., 1989). Unfortunately this is not always the case, as new player tracking technologies are often released with little if any evidence of the system's validity and reliability provided by the manufacturer (Edgecomb et al., 2006). Consequently, researchers must independently assess the accuracy and reproducibility of newly released technologies in a range of sport-specific contexts. For industry to confidently interpret and use GPS data to inform practice (e.g. prescribe, monitor or alter training), its accuracy, reproducibility and practical utility needs examining (Scott et al., 2016). Chapter 4 will examine the sensitivity, reliability and convergent validity of wearable GPS with integrated intertial sensors for quantifying the peak intensities of rugby. The following sections will review relevant wearable technology validity and reliability literature.

2.5.3 Validity

Validity refers to the degree that an instrument accurately measures what it intends to measure (Atkinson et al., 1998). Thus, player tracking technologies ought to accurately quantify an athlete's position, in addition to the resultant displacement, velocity and acceleration when compared to a criterion measure. Early player tracking technologies were rarely tested for their validity due to a lack of a criterion measure to compare them to (Reilly, 1976). In fact, there has been much deliberation in the literature as to what the best criterion measure is to assess player tracking systems validity and this has evolved over time with technological advancements.

Various criterion measures have been used to validate player tracking technologies, such as pre-defined courses (Coutts et al., 2010a), pre-defined courses with infra-red timing gates (Jennings et al., 2010), laser devices (Varley et al., 2012b) and three-dimensional (3D) motion analysis systems (Richards, 1999). However, pre-defined courses measured by timing gates and laser devices are poor criterion measures with little ground truth for team sport contexts. The current “gold-standard” or accepted criterion measure for assessing human position, distance, speed and acceleration during both linear and non-linear trials are 3D motion analysis systems (Richards, 1999; Windolf et al., 2008). Briefly, these 3D systems comprise several high-resolution cameras that have a very high sampling frequency to capture a visual record of light-reflective markers that are placed on specific anatomical landmarks of an individual. The position, displacement and velocity of the individual is then calculated by digitising multiple frames of the markers. The number and configuration of the high-resolution cameras, sampling rate, marker properties and calibration procedures all influence positional accuracy, however Vicon (i.e. a 3D motion analysis system) has reported an error range of within one millimetre dependent upon the aforementioned variables (Windolf et al., 2008). Vicon has been used as a criterion measure to validate numerous athlete tracking systems, including GPS (Duffield et al., 2010) and local positioning-systems (LPS) in soccer (Stevens et al., 2014a) and netball (Sweeting, 2017), which are also radio-frequency based.

The statistical methodology used to quantify the validity of player tracking technologies has also differed widely between studies, making comparisons between studies difficult. The validity of an instrument may be statistically presented and interpreted using the standard error of the estimate (SEE), typical or standard error of measurement (TEM/SEM), the coefficient of variation (CV), percentage difference from the criterion measure (Scott et al., 2016), correlation coefficient (*r*), Bland-Altman plot (Atkinson et al., 1998) or linear regression (Hopkins, 2004).

Bland and Altman (Bland et al., 1986) realised that many researchers were misusing the correlation coefficient as a measure of validity, believing that it was the most important or only measure of the relationship between two measures (Hopkins, 2004). The issue is that two measures may be highly correlated as shown by a correlation coefficient ($r > 0.80$), yet the two measures may considerably differ across their range in values. Bland-Altman plots highlight such differences to explicitly illustrate differences between the two measures (plotted on the *y* axis) over their range (plotted on the *x* axis) (Hopkins, 2004). Subsequently, the direction and magnitude of the scatter around the zero line may be used to identify heteroscedasticity, random error and bias (Atkinson et al., 1998). However, Bland-Altman plots incorrectly indicate that there are systematic errors or bias in the relationship between a practical instrument and a criterion measure, when one has been calibrated against the other (Hopkins, 2004). Alternatively, regression analysis of the criterion vs the instrument revealed no bias. If bias did develop or if random error changes arose since the last calibration then regression analysis equations can correct the raw values to recalibrate the instrument. Regression analysis is recommended in favour of Bland-Altman plots when trying to estimate the true value of something that has been measured with a less than perfect practical instrument (Hopkins, 2004, 2010). Consequently, linear regression analysis should be used to understand the error of an athlete tracking technology (i.e. practical instrument) when compared to a criterion or "gold-standard" measure (e.g. 3D motion analysis systems) (Sweeting, 2017).

Player tracking technologies provide valuable objective data on player activity profiles and evaluating physical performance, both between and within individuals of various playing positions (Cummins et al., 2013). Large measurement error of player tracking technologies may result in activity profile data being misinterpreted, potentially leading to under- or over-training of athletes (Delaney, 2016). Consequently, player match performance may be adversely affected via a misbalance of fitness and fatigue (Banister et al., 1975). Thus, the validity of player tracking technologies is of utmost importance to help ensure appropriate interpretation and application of the data. In order for technology to be valid, it must also be reliable (Baumgartner, 1989).

2.5.4 Reliability

Reliability refers to the ability of a measurement tool to accurately reproduce measurements given identical circumstances (Baumgartner, 1989; Hopkins, 2000). Improved reliability infers greater precision of single measurements and better tracking of changes in measurements in both research and practical settings (Hopkins, 2000). A measurement tool may accurately reproduce measurements that are not valid (i.e. be reliably invalid). Thus, a measurement tool may be deemed reliable without being valid, though for the tool to be considered valid, it must be reliable (Baumgartner, 1989). Given practitioners and researchers use player tracking technologies to monitor and prescribe training based upon changes in physical output of an individual or compare activity profiles between players, positions, matches, levels of competition or sporting codes, it is critical that player tracking systems are reliable (Drust et al., 2007).

Understanding the reliability of a given technology (e.g. GPS) enables practitioners to confidently monitor changes within and between individuals during training and competition to guide practice. To do this, the inter (between) and intra (within) GPS receiver reliability need to be established. Intra-receiver reliability refers to the ability of a single GPS receiver to produce accurate information consistently, which is critical when making comparisons between training sessions or matches for the same player. Inter-receiver reliability assesses the accurate reproduction of measures between multiple GPS receivers, which is incredibly important for activity profile comparisons both between players and between sessions (Scott et al., 2016).

Reliability is typically evaluated using the change in the mean, typical or standard error of measurement, often expressed as a percent of the mean score; coefficient of variation (CV) or via test-retest correlations (intra-class correlation coefficient; ICC) (Hopkins, 2000). The following paragraphs will briefly explain some statistical approaches to quantifying and interpreting reliability.

The change in the mean is the difference between test means. It is comprised of random change and systematic change. Random change is due to sampling error and is smaller in larger sample size studies, as the random errors from a greater number of measurements leads to the errors inevitably cancelling each other out above and below the mean to be closer to zero. Systematic changes on the other hand are non-random changes in the mean between two or more trials. Examples of systematic changes that are particularly important in human research trials are learning effects, motivation and fatigue (Hopkins, 2000). To be sure that an intervention (e.g. training or diet change) is having a true or real effect, it is critical to account for such systematic effects by implementing familiarisation trials, enough time between trials and strictly standardising procedures to ensure any systematic changes are negligible before administering the intervention (Hopkins, 2000). When assessing whether a change in the mean is a reproducible systematic effect, you can set and calculate the compatibility limits for the mean (usually 95%), which represent the likely range of the 'true' or systematic population change (Hopkins, 2000).

Typical error represents the typical variation in an individual's value from one measurement to another, often termed the within-subject standard deviation. All statistical methodologies for calculating the typical error hinge on the assumption that the typical error is of the same magnitude for every individual. If this is not the case and the typical error varies from subject to subject, the data are said to display heteroscedasticity, or non-uniform error (Hopkins, 2000). Non-uniform error results in an average typical error that is too high for some individuals and too low for others. To account for heteroscedasticity, separate analyses may be performed for groups of subjects that have similar typical errors (e.g. positional groups) or transform the variable to make its error uniform. Log transformation is a popular methodology for making error uniform when larger values of a given measure have more error. Non-uniform error should be assessed whenever reliability statistics are calculated (Hopkins, 2000). Expressing the typical error as a percentage of the subject's mean score is known as the coefficient of variation. For most athletic events the CV is between 1-5% and depend largely on the nature of the sporting event, athlete experience and the time elapsed between events (Hopkins, 2000). A scale for interpreting the reliability of a measure expressed as the CV is: good (< 5%), moderate (5-10%), or poor (> 10%) (Hopkins, 2000).

Pearson correlation coefficients are acceptable for use with test-retest reliability for two tests, but with small sample sizes they overestimate the true correlation (Hopkins, 2000). Intraclass correlation coefficients (ICC) do not suffer from a similar bias with small sample sizes and may be calculated as a single correlation value when two or more trials are involved. Both forms of correlations are not affected by any changes in the mean between trials. The ICC is comparable to the Pearson correlations between all pairs of trials when appropriately averaged (Hopkins, 2000). Magnitudes of ICCs are evaluated using the following thresholds: > 0.99, extremely high; ≤ 0.99 to ≥ 0.90, very high; <0.90 to ≥ 0.75, high; < 0.75 to ≥ 0.50, moderate; < 0.50 to ≥ 0.20, low; < 0.20, very low (Hopkins, 2015). Now that the constructs of validity and reliability have been explored, the following sections will discuss the validity and reliability of GPS for quantifying football code activity profiles.

2.5.5 GPS Validity & Reliability

There has been a plethora of research conducted examining the validity and reliability of GPS for quantifying the activity profile of a range of team sports (Coutts et al., 2010a; Jennings et al., 2010; Johnston et al., 2013; Johnston et al., 2012; Varley et al., 2012b; Vickery et al., 2013). Comparing the validity and reliability of GPS for measuring distance is difficult due to the differences in the equipment used (e.g. GPS model, criterion measure) and the movement task performed (i.e. distance, speed and linearity) (Varley, 2013). That being said, the available literature suggests that all GPS receivers are capable of tracking an athlete's distance during team sport movements with adequate validity and intra receiver reliability regardless of sampling rate (1, 5, 10, 15 Hz) (Scott et al., 2016). Originally, GPS devices operated with a sampling rate (i.e. speed the GPS device receives satellite signals) of 1 Hz (i.e. one sample per second). An increased GPS sampling rate should rationally improve the precision of the device to measure short, rapid movements such as accelerations that frequently occur over very short durations (Bangsbo et al., 1991). Practically speaking, valid distance estimates means that all GPS devices may be used to quantify player distances covered during training and competition, with accuracy of results viewed with confidence. However, earlier GPS models sampling at 1 or 5 Hz are limited when assessing distance during high-intensity running, velocity measures and short linear running and results should be interpreted with caution (Scott et al., 2016).

Increasing GPS receiver sampling rate from 1 Hz to 10 Hz generally delivers superior measurement accuracy, whilst a further increase to 15Hz yields no additional benefit (Scott et al., 2016). In fact, there is some evidence to suggest that 15 Hz may be detrimental to measures of distance and speed (Johnston et al., 2013; Scott et al., 2016). Most available research suggests that 10 Hz GPS devices can validly measure distances covered during both linear and team sport simulated circuits across various running speeds and distances (Scott et al., 2016). However, the validity and reliability of GPS devices to measure team sports activity seems inversely related speed of movement. For example, the validity of GPS for measuring distance covered during very high-speed running has been reported as poor (CV = 11%) (Rampinini et al., 2015). In addition, distance measurements from a 10 Hz GPS receiver were significantly different from the VICON criterion measurement during a short running course that incorporated several tight changes of direction (Vickery et al., 2013). Similarly, peak speed measures were significantly higher than a criterion measure during a team sport simulated circuit (Johnston et al., 2013), suggesting that 10 Hz GPS devices may overestimate athlete peak speeds during team sport matches. Further, typical error of measurement (TEM) increased for both 10 and 15 Hz GPS devices as speed of movement increased during the team sport simulated circuit (0.8-20%) (Johnston et al., 2013). Lastly, 10 Hz GPS devices poorly estimate instantaneous velocity when very high accelerations (> 4 $m.s^{-2}$) are occurring during team sports (Akenhead et al., 2014).

The reproducibility of distance and speed estimates via GPS is often better from one measurement to the next within a device (intra receiver reliability), than between devices (inter receiver reliability) irrespective of sampling frequency (Scott et al., 2016). Ten hertz GPS devices display good intra receiver reliability (CV < 5%) for assessing measures of distance during 15 and 30 m sprints (Castellano et al., 2011). Due to the improved intra receiver reliability and relatively poorer inter receiver reliability, it is recommended that athletes are assigned the same receiver when tracking player movement across multiple sessions (Buchheit et al., 2014).

Similar to GPS device validity estimates, the reliability of GPS devices for measuring distance is inversely related to the speed of movement and rate of acceleration. For instance, good inter receiver reliability was reported for total distance covered (TEM = 1.3%, ICC = 0.51), low-speed (0-13.99 $km.h^{-1}$) running distance (TEM = 1.7%, ICC = 0.97), and high-speed (14-19.99 $km.h^{-1}$) running distance (TEM = 4.8%, ICC = 0.88) measured by 10 Hz GPS devices. As running speed increased to very high-speed running (> 20 $km.h^{-1}$), inter receiver reliability dramatically declined (TEM = 11.5%) (Johnston et al., 2013). Therefore caution should be applied when comparing and interpreting high-speed running between GPS devices (Scott et al., 2016).

Inter receiver reliability improves across all GPS devices when measuring team sport simulations, allowing practitioners to be able to confidently compare player movement data between sessions. Though, inter receiver reliability degrades during both linear/curvilinear and team sport simulated circuits at high-speed running (Scott et al., 2016). The weight of evidence suggests that 10 Hz GPS devices are the most reliable in comparison with 1 Hz or 5 Hz devices, possessing good to moderate intra receiver reliability. When measuring instantaneous velocity 10 Hz GPS devices have good to moderate inter receiver reliability during running involving accelerations (CV = 1.9-4.3%), constant velocity running (CV = 2-5.3.0%), or running incorporating decelerations

(CV = 6%) (Varley et al., 2012b). Moreover, regardless of the initial velocity of running

10 Hz GPS devices can reliably reproduce instantaneous velocity measurements. Indeed, inter receiver reliability improves as initial velocity of movement increases during both constant velocity running and running involving accelerations. In fact, whilst sprinting over ten meters 10 Hz GPS devices have good inter receiver reliability (CV = 0.1-9.1%) for measuring instantaneous velocity over a large range of acceleration magnitudes, although reliability declined with increased rates of acceleration (Akenhead et al., 2014). Finally, measurement of peak speed during a team sport simulated circuit using 10 Hz GPS devices has shown good inter receiver reliability (TEM = 1.6%, ICC = 0.97) (Johnston et al., 2013).

2.5.6 Metabolic Power

Metabolic power is a GPS-derived measure of power that considers the energetic cost of accelerated running on flat terrain to be energetically analogous to running on an equivalent uphill slope at a constant speed (Di Prampero et al., 2005). Instantaneous metabolic power output ($W.kg^{-1}$) of an individual may subsequently be calculated if acceleration and velocity are known (Di Prampero et al., 2005; Osgnach et al., 2010). The metabolic power model (Di Prampero et al., 2005) with adaptations (Osgnach et al., 2010) provides a method for measuring the activity profile or external load of team sport competition, as it accounts for accelerations, decelerations and speed-based movements (Delaney et al., 2016a; Osgnach et al., 2010).

The average metabolic power has been reported during AFL (9.2-10.9 $W.kg^{-1}$) (Coutts et al., 2014) and rugby league (8.2-9.0 $W.kg^{-1}$) (Kempton et al., 2015c) competition, alongside during soccer training (7.5-8.4 $W.kg^{-1}$) (Gaudino et al., 2013). Findings across the football codes illustrate that metabolic power analysis complements ‘traditional’ speed-based running metrics, as many movements that do not exceed high-speed running thresholds (i.e. accelerations and decelerations) are very energetically demanding and should be quantified (Coutts et al., 2014; Gaudino et al., 2013; Kempton et al., 2015c; Stevens et al., 2014b).

Support for the application of metabolic power is evident when examining high-intensity periods during training and competition (Gaudino et al., 2013). Given that metabolic power is approximately 20 $W.kg^{-1}$ when running at a constant speed of 14.4 $km.hr^{-1}$ on grass (Osgnach et al., 2016), the extent that speed-based measures underestimate the 'true' energy cost of high-intensity activity may be studied via comparison of distance covered above 14.4 $km.hr^{-1}$ (i.e. common high-speed threshold) to the distance covered above 20 $W.kg^{-1}$. During soccer training, 13% of the total distance was covered above 14.4 $km.hr^{-1}$ compared to 19% above a metabolic power of 20 $W.kg^{-1}$, indicating a ~ 6% underestimation of energy cost via traditional speed-based measures (Gaudino et al., 2013). During soccer competition, 18% of the total distance was covered above the high-speed running threshold of 14.4 $km.hr^{-1}$, compared to 26% above a metabolic power of 20 $W.kg^{-1}$, representing an ~ 8% underestimation of energy cost via high-speed running distance (Osgnach et al., 2010). These differences between high-speed running and high metabolic power distances pale in comparison to during rugby league competition, where using the same thresholds for both measures, high-speed running underestimated energy cost by 37-76% (ES: 1.3-3.0) depending on playing position (Kempton et al., 2015c). Whilst metabolic power presents an ecologically valid premise providing a representative measure of both speed and acceleratory movements common to football codes, it has many limitations.

1. Any measure that summates multiple measures will inherently sum measurement errors too. Since all GPS devices have reduced accuracy for measuring short distance,

high-speed or acceleratory movements, the increased error of measurement will concurrently be observed within metabolic power estimates.

2. Creating one 'magic bullet' metabolic power number masks the underlying mechanism of the external load (i.e. accelerated running or high-speed running) (Buchheit et al., 2015).

3. In the mathematical model, the overall mass of the athlete is assumed to be located at their centre of mass, thereby disregarding the contribution of the limbs to the energetics (Di Prampero et al., 2005). This is equivalent to assuming that the energetic cost of running uphill at a constant speed is the same as sprinting up an equivalent slope, which is unlikely.

4. The energetic cost model (Di Prampero et al., 2005) incorrectly implies that the frequency of movement is the same during both accelerated running on flat vs. uphill terrain (Osgnach et al., 2010).

5. The model calculates the average force by active muscles during ground contact (one foot) and neglects frontal plane contributions (Di Prampero et al., 2005). Moreover, the model erroneously assumes that the joint angles and forces during the landing phase of a gait cycle are the same during uphill running at a constant speed and during sprinting at an equivalent slope (Di Prampero et al., 2005).

6. Original model calculations were based on the energy cost of treadmill running at different constant speeds and inclines of -0.45 to +0.45 (Minetti et al., 2002), which are much less than the inclines (equivalent slopes) reported whilst maximally accelerating and sprinting (+0.70) (Di Prampero et al., 2005). Therefore, the validity of values for slope inclines greater than 0.45 is based on the assumption that the relationship between slope incline and energy cost of running holds true beyond 0.45.

7. The energy cost equation was derived from direct oxygen uptake measurements during aerobic steady state exercise at constant speeds (Minetti et al., 2002). Energy sources during sprint running are largely anaerobic and thus energetic costs and metabolic power estimates should be considered with caution (Di Prampero et al., 2005).

8. The calculation for the equivalent slope of accelerated running is compared to running at a constant speed on flat terrain where the equivalent slope is assumed to be zero. Yet humans have a small forward lean whilst running, even at low speeds (Di Prampero et al., 2005). The model assumes that the equivalent slope and equivalent mass values are in excess of those during constant speed running and the average force required to move the athlete's body mass is equal to that prevailing under the Earth's gravitational field (Di Prampero et al., 2005). These assumptions should not introduce substantial error into energy cost and metabolic power estimates though, since the model's reference value was the energy cost of constant speed running per unit of body mass (Di Prampero et al., 2005).

9. The initial energetic model (Di Prampero et al., 2005) neglected the known energy required to overcome air resistance. Although alterations to equations can be made to account for air resistance where required (Di Prampero et al., 2015).

10. The model calculates energy expenditure from speed and acceleratory locomotor movements, but is unable to quantify many energetically taxing non-locomotor movements such as tackling, kicking, throwing or jumping that frequently occur in the football codes (Brown et al., 2016; Buchheit et al., 2015; Highton et al., 2016; Stevens et al., 2014b).

Despite several limitations of the metabolic power model (Di Prampero et al., 2005), it has many benefits compared to speed-based methodologies. Many factors may restrict a player's ability to cover distances at high-speeds during competition such as spatial constraints, rules of the game and positional role etc. Therefore, the metabolic power model gleans novel insights into the bioenergetics of accelerations and decelerations, providing coaches with a more holistic picture of the external loads of competition when compared to the sole use of speed-based measures. Yet, to be used confidently in practice the validity of the metabolic power model must be assessed.

Locomotor related metabolic power measured by either GPS or local positioning systems (LPS) differs substantially from the true metabolic demands as measured by indirect calorimetry ($\dot{V}O_2$ measures, PVO_2) (Brown et al., 2016; Buchheit et al., 2015; Highton et al., 2016; Stevens et al., 2014b). Table 2.3 illustrates that metabolic power grossly underestimates the energetic cost of exercise that is intermittent in nature, including shuttle running (Stevens et al., 2014b), soccer (Buchheit et al., 2015), rugby (Highton et al., 2016) and field sport specific circuits (Brown et al., 2016).

Table 2.3 Exercise energy cost comparison between indirect calorimetry ($\dot{V}O_2$) and Global or Local Positioning Systems using metabolic power equations (Di Prampero et al., 2005; Osgnach et al., 2010).

Authors	**Exercise Task**	**Velocity** (km.hr^{-1})	**GPS/LPS - $\dot{V}O_2$ derived** (%)
(Stevens et al., 2014b)	Continuous running Shuttle running	7.5-10	+ 6 to 11% -13 to -16%
(Buchheit et al., 2015)	Soccer specific circuit	6.5-7.5	-29 ± 10% during exercise, -85 ± 7 % during recovery
(Highton et al., 2016)	Rugby specific circuit	9-14.4	-45%
	Walking Jogging Running	4 8 12	+43% -7.8% -4.8%
(Brown et al., 2016)	Field sport circuit	Self-selected	-44%

Negative energy cost percentage differences indicate positioning systems underestimated the energy cost of exercise when compared to indirect calorimetry.

Using portable gas analysers and local positioning systems (500 Hz) to measure the energy cost of constant and shuttle running at six different speeds (7.5-10 km.hr^{-1}) in soccer players, GPS derived metabolic power overestimated (6-11%) measured energy cost via gas analysis during constant running. Conversely metabolic power significantly underestimated (-13 to -16%) energy cost of shuttle running when compared to direct gas analysis (Stevens et al., 2014b). During a soccer specific circuit, Metabolic power measured via 4 Hz GPS devices was 29 ± 10% lower than P$\dot{V}O_2$ measured via portable gas analysers during 1 minute exercise bouts at speeds of 6.5, 7 and 7.5 km.hr^{-1} and 85 ± 7% lower during 30 second passive recovery periods (Buchheit et al., 2015). During a 90 minute exercise session (30 minutes exercise, 60 minutes recovery) that comprised of 6 × 5 minute randomised bouts of walking, jogging, running or a field sport circuit separated by 10 minutes of recovery, energy cost estimates were compared between GPS (5Hz, interpolated to 15 Hz) and portable gas analysis (Brown et al., 2016). Similar to previous findings comparing direct and indirect energy cost estimates, metabolic power was significantly lower ($p < 0.01$) and underestimated to a moderate extent (19%) over the entire 90 minute exercise session. When assessing the randomised bouts within the session, no substantial differences were observed during jogging (7.8%) or running (4.8%). However, GPS overestimated metabolic power to a very large extent during walking (43%) and underestimated all field sport circuits to a very large extent (-44%, $p < 0.01$) compared to P$\dot{V}O_2$ derived energy cost measurement (Brown et al., 2016). During a rugby specific circuit involving three sets of 6 × 8 meter runs at 4 m.s^{-1} (14.4 km.hr^{-1}) with 60 seconds standing recovery between each set, metabolic power was underestimated by GPS (10 Hz) when compared to open circuit spirometry (Highton et al., 2016). Energy cost was systematically underestimated (-5.94 ± 0.67

kcal.min^{-1}) by GPS during the rugby specific circuit (7.2 ± 1.0 kcal.min^{-1}) compared to open circuit spirometry (13.2 ± 2.3 kcal.min^{-1}) (Highton et al., 2016).

Altogether, GPS derived metabolic power largely underestimates the energy cost of intermittent exercise, especially during recovery periods. The underestimation of energy cost during intermittent exercise may be due to a host of limitations and assumptions of the metabolic power model (Di Prampero et al., 2005; Osgnach et al., 2010), as previously discussed in this chapter. For example, GPS derived metabolic power is unable to measure the energy cost from accelerations or decelerations associated with physical contact or static exertions (Highton et al., 2016). Another explanation for the gross underestimation of energy expenditure during intermittent exercise is that GPS is unable to quantify excess post-exercise oxygen consumption (EPOC) during periods of rest (Buchheit et al., 2015; Highton et al., 2016). The large divergence between estimated energy cost via GPS or LPS compared to direct measurement via portable gas analysis, illustrates that Metabolic power is not a valid measure during intermittent exercise incorporating rest periods, however it does provide a reasonably accurate estimation of continuous low speed movement.

Despite poor validity for measuring intermittent exercise, metabolic power has been suggested to be of use as a global indicator of external load, encompassing accelerated, decelerated and speed-based running (Delaney et al., 2016a). Justifying this view, metabolic power displayed good accuracy when compared to a criterion method (radar) utilising both 5 Hz (CV = 4.5%) and 10 Hz (CV = 2.4%) GPS devices (Rampinini et al., 2015). Moreover, distances covered above high (> 20 W.kg^{-1}) and very high (> 35 W.kg^{-1}) metabolic power thresholds exhibited comparable or reduced variability when compared to high-speed running distances (CV = 4.5-12% vs. 4.7-23%) (Rampinini et al., 2015). During the peak intensity periods of rugby league competition, metabolic power was greater for hookers, half-backs and fullbacks compared to middle forwards and outside backs (Delaney et al., 2016a). Further, the way in which players accumulated metabolic power (i.e. via acceleratory or speed-based movements) differed between playing positions, providing coaches with valuable information that may aid training monitoring and prescription. Although metabolic power should not be used in isolation as a measure of external load as the combination of acceleratory and speed-based running into one metric masks the underlying mechanism of the load (Buchheit et al., 2015)

In conclusion, increasing the sampling rate of GPS receivers appears to improve the validity and reliability for measurement of distance and speed during both linear, non-linear and team sport-simulated activities. Whilst GPS athlete tracking data can be of great value to practitioners, it has reduced validity and reliability for quantifying rapid changes of direction (Rawstorn et al., 2014) and velocity (Akenhead et al., 2014; Jennings et al., 2010), estimating metabolic power (Buchheit et al., 2015) and for assessing short duration, high-velocity tasks that frequently occur in team sports (Coutts et al., 2010a; Jennings et al., 2010). As GPS receivers rely on satellite communication, they are not able to quantify athlete activity profiles indoors. Movements that incur little horizontal displacement (e.g., collisions, tackles, kicking, jumping, throwing) are also likely to be underestimated by GPS (Boyd et al., 2013). Considering several football codes are characterised by engaging in or evading contact and success is heavily dependent on tackling ability (Gabbett, 2013b), it is not too speculative to suggest that the activity profile or external load may have been substantially underestimated (Coughlan et al., 2011; Cunniffe et al., 2009) via the use of GPS technology alone (Boyd et al., 2013). Practitioners must interpret high-speed and acceleratory GPS estimates with caution when making training monitoring and prescription decisions.

Quantification of all movements that take place in football codes may require the use of additional technologies such as accelerometers to better inform the training process.

2.5.7 Accelerometers

Accelerometers can quantify the frequency and magnitude of acceleration (Hendelman et al., 2000a). Kinetic (motion) energy as measured by accelerometers can be converted into electrical energy and subsequently translated and recorded by the receiver as acceleration measurement data (Boyd, 2011). Processed data is subsequently recorded via internal memory and then may be downloaded to computers for further analysis, interpretation and practical use. Accelerometers are highly responsive motion sensors that measure acceleration based upon English physicist Isaac Newton's elementary second law of motion: Force (N) = mass (kg) × acceleration ($m.s^{-2}$) (Newton, 1687). The equation may then be rearranged to calculate acceleration (i.e. acceleration = Force / mass). Acceleration is measured in gravitational acceleration units (i.e. *g*; $g = 9.8\ m.s^{-2}$) (Chen et al., 2005). Put simply, accelerometers measure accelerations by sensing how much a mass moves when a force acts on it, not by calculating how speed changes over time (i.e. acceleration = Δ speed / time). More specifically, when the accelerometer is moved, the acceleration of a seismic mass inside the receiver presses on a piezoelectric sensing element (potentiometer) that the mass is attached to (Figure 2.6) (Chen et al., 2005). The sensing element subsequently produces an electrical voltage output proportional to the applied acceleration (Nedergaard et al., 2015). When acceleration is zero, the body of interest is no longer changing its speed, yet it may still be moving at a constant speed. As acceleration is proportional to the net external force involved and thus more directly reflective of energy costs, measurement of physical activity using acceleration is preferred to using speed (Chen et al., 2005).

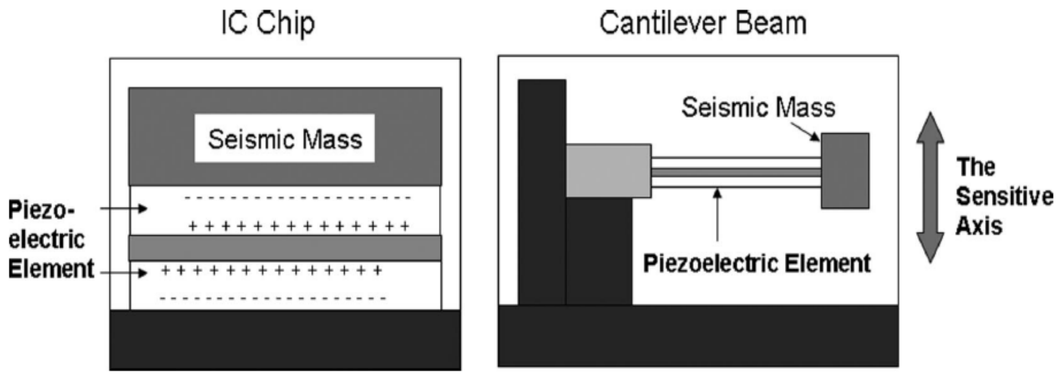

Figure 2.6 Schematic of the two common piezoelectric accelerometer configurations. During acceleration, the seismic mass causes the piezoelectric element to change shape either by bending beam sensors (right-hand image), or by direct tension or compression in integrated chip (IC) sensors (Chen et al., 2005).

Accelerometer technology is not new, with the earliest commercialised model credited to McCollum and Peters in the 1920's (McCullom et al., 1924; Walter, 1999) and the first model specifically designed for measuring human movement was invented in the 1950's (Inman et al., 1953). There are many different types of accelerometers used for a wide range of applications across industry and science. Piezoelectric accelerometers (Figure 2.6) are commonly used to measure human locomotion as they are unrivalled in terms of their high sampling frequency range (typically 100 Hz with criterion range: 1-10,000 Hz), thereby allowing more accurate measurement of rapid movements. Piezoelectric accelerometers have additional benefits such as light packaged weight and temperature range (Levinzon, 2015). To ensure that rapid human movements (e.g. maximal accelerations) are accurately quantified by accelerometers, its sampling frequency should be at least twice the frequency of the highest frequency movement measured, known as the Nyquist criterion (Oppenheim et al., 1983). Having these characteristics alongside having high outputs for small strains and the potential of a large dynamic range (Togowa et al., 1998) make piezoelectric accelerometers ideal for quantifying the physical activity of humans. Whilst piezoelectric sensors can be reliably used to measure dynamic movements, their ability to measure static loading (e.g. rugby scrum) is limited. This can be explained by a phenomenon known as leakage, whereby the initial change in charge in the piezoelectric element dissipates over time, even if the static loading that produced the initial change is still present (Togowa et al., 1998). Initially accelerometers were used to count the frequency of accelerations that occurred within a set time period (Rowlands, 2007). Both uni-axial (measure one axis of movement) and tri-axial (measure three axes) accelerometer models have been widely used to measure human physical activity across many subject populations and during numerous exercise tasks (Fudge et al., 2007; Steele et al., 2000). As the name suggests, tri-axial accelerometers measure accelerations in three axes: mediolateral (sideways-x), anteriorposterior (forwards/backwards-y) and craniocaudal (vertical-z). Although the premise of calculating a vector magnitude derived via the summation of acceleration in three dimensions that accounts for both the frequency and magnitude of movement has been around since the 1960's (Cavagna et al., 1961), it's wide spread adoption occurred much later, now commonly referred to via proprietary names such as PlayerLoad™ or BodyLoad™.

Manufacturers of accelerometer technology used by sporting practitioners and scientists have created modified vector magnitude proprietary algorithms, with frequently published measures being PlayerLoad™ (Catapult Sports) (Boyd et al., 2013) and BodyLoad™ (GPSports) (Weaving et al., 2014). Vector magnitudes provide an estimate of the totality of physical movement, often referred to as external load. The vector magnitudes are mathematically expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in three orthogonal planes accumulated over time or sampling interval (i.e. 100 Hz):

PlayerLoad™ or Bodyload™ = $\sqrt{(\Delta Forward^2 + \Delta Side^2 + \Delta Up^2)}$, where Forward, Side and Up refer to directions of acceleration, and Δ refers to the change over the sampling interval (10 ms).

Seminal accelerometer research focused on the validity and reliability of the receivers (Nichols et al., 1999), followed by using the technology to measure physical activity levels of various populations, including youth (Eston et al., 1998), aging (Sumukadas et al., 2008) and diseased (Steele et al., 2000). Research examining tri-axial accelerometers ability to estimate energy expenditure (Jakicic et al., 1999) and to measure human locomotion in a variety of populations prompted further investigations of the receivers in sporting populations (Boyd et al., 2010; Gabbett et al., 2011b; Montgomery et al., 2010; Wixted et al., 2007). The first application of tri-axial accelerometers for the measurement of elite sporting movement was in 2007 (Wixted et al., 2007). The following sections will provide a synopsis of accelerometer research, with a focus on the validity, reliability and utility of tri-axial accelerometers to track player movement within football codes.

2.5.8 Accelerometer Validity & Reliability in Football

Considering there are several types of accelerometers (e.g. piezoelectric, piezoresistive, capacitive), positioned on humans in many locations (e.g. hip, head, trunk), that measure acceleration in multiple planes (uni-, bi-, tri-axial) for multiple purposes (e.g. gait analysis, classify movements, estimate energy expenditure or external load), discussion of all is not feasible nor relevant for the purpose of this thesis. Consequently, subsequent sections will chronologically discuss accelerometer validity and reliability through the prism of piezoelectric tri-axial accelerometers housed within commercially available GPS receivers designed for quantifying athletic movement.

Accelerometers are commonly used to objectively measure impacts (i.e. high-intensity movements involving a rapid change of acceleration), providing coaches with information that may help them to plan and prescribe subsequent recovery and training (Gastin et al., 2013; Kelly et al., 2012; McLellan et al., 2012). Impacts were the focus of an investigation examining the validity of a commercially available accelerometer to measure impacts during jumping and landing tasks that commonly occur in field based team sport contexts (Tran et al., 2010). Ten participants completed a drop-landing task from a range of heights (30-50 cm) and a counter movement jump. Peak acceleration quantified by a tri-axial accelerometer sampling at 100 Hz embedded within a GPS receiver (SPI Pro, GPSports Pty Ltd, Australia) was compared to vertical ground reaction force measured by a portable force plate (model ACG, Advanced Mechanical Technologies Inc., USA) sampling at 100 Hz, acting as the criterion measure. All accelerometer derived peak accelerations were moderately correlated (r = 0.45-0.70, p < 0.05) yet they were significantly higher than criterion vertical ground force reaction values adjusted for body weight. Raw acceleration was highly variable (CV > 20%), although smoothing the data reduced error margins (CV = 11-22%) (Tran et al., 2010). Findings indicated that although raw accelerometer values displayed large error, smoothed accelerometer data improves accuracy and efficacy for the quantification of jumping-based impacts.

To assess the within- and between-receiver reliability of tri-axial accelerometers (100 Hz) in a laboratory setting, eight accelerometers (MinimaxX 2.0, Catapult, Australia) were fixed to a hydraulic universal testing machine (Instron 8501) and mechanically shaken (dynamic condition) at 0.5 g and 3.0 g in addition to a static assessment (Boyd et al., 2011). The accelerometer derived vector magnitude PlayerLoad^{TM} displayed acceptable within- (dynamic: CV = 0.91-1.05%; static: CV =

1.10%) and between-receiver (dynamic: CV = 1.02-1.04%; static: CV = 1.10%) reliability.

To assess the between-receiver reliability of accelerometers in the field, the same research group instrumented 10 semi-professional AFL players with two receivers inserted into a custom made tightly fitted vest located on the posterior side of the upper torso between the scapulae during competitive matches. Similar to findings in the laboratory, during Australian football matches the accelerometers between-receiver reliability was acceptable (CV = 1.9%). The noise (CV = 1.9%) of accelerometer derived PlayerLoad™ was lower than the smallest worthwhile difference (SWD) or signal (SWD = 6%). The MinimaxX tri-axial accelerometer demonstrated good (CV < 5%) within- and between-receiver reliability during laboratory conditions and good between-receiver reliability during competitive AFL matches. Therefore, authors concluded that these accelerometers may be used with confidence in the field as a reliable tool to measure physical activity in team sports, between players and competitive matches. The much lower noise of PlayerLoad™ when compared to the signal, indicates that accelerometers are sensitive to detecting changes or differences in physical movement during Australian Rules Football competition (Boyd et al., 2011).

Accelerometers are valid tools for quantifying the frequency and magnitude of collision during professional rugby league training (Gabbett et al., 2010). Collisions were detected using tri-axial accelerometers housed within a GPS receiver also comprising magnetometers and gyroscopes (MinimaxX, Catapult Sports, Melbourne, Victoria) and compared to video based coding of actual events (criterion measure) during training. The accelerometers and gyroscopes (measures orientation) housed within the GPS receiver were used to detect collisions. In order for a collision to be detected, the receiver worn between the player's scapulae had to be moved into a non-vertical position (i.e. the player was leaning forwards, backwards, to the left or to the right). Further, a spike in the instantaneous PlayerLoad™ immediately before the change in orientation of the receiver was required for collision detection. The magnitude of each collision were categorised as mild, moderate or heavy. A mild collision was defined as contact made with a player but they were able to continue forward progress/momentum out of a tackle. Moderate collisions were defined as contact made with player, forward progress/momentum continued until tackled. Lastly, heavy collisions were defined as contact made with a player, with forward progress/momentum stopped, and forced backwards in the tackle. The MinimaxX receiver was an ecologically valid tool for detecting the frequency and magnitude of mild (r = 0.89), moderate (r = 0.97) and heavy (r = 0.99) collisions, displaying very high relationships with video based coding (Figure 2.7) (Gabbett et al., 2010). Whilst accelerometer validity for detecting the frequency and magnitude of collisions during training was promising for its efficacy within football codes, translation to validity during competition was yet to be examined.

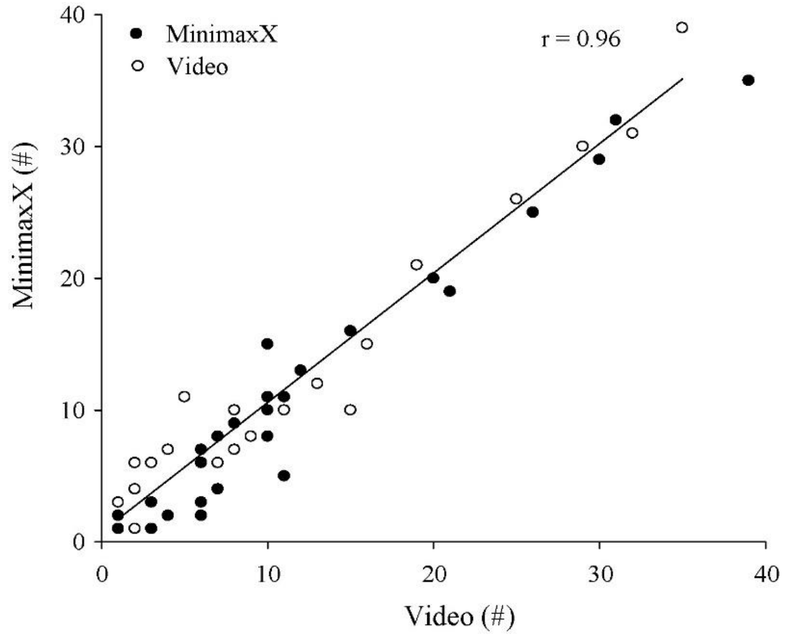

Figure 2.7 Comparison of MinimaxX and video methods for recording collisions. Reproduced from (Gabbett et al., 2010). Data are recorded as counts for 'video' and 'MinimaxX' tackle detection methods. Each data point on the figure represents the individual player collisions coded from video and recorded via MinimaxX.

Body worn tri-axial accelerometers (i.e. SPI Pro GPSports Systems, Canberra, ACT, Australia) sampling at 100 Hz are capable of accurate automatic detection of tackles and collisions during professional rugby competition without video assessment (Kelly et al., 2012). Such data may provide valuable information to practitioners given the importance of tackling in football codes and its association with injury risk. A combination of different non-linear pattern recognition techniques; 1. support vector machine and 2. hidden conditional random field models were used to classify rugby union tackles during competition. These machine learning techniques were selected to learn and understand the relationship between the source data (i.e. acceleration signals) and the target data (i.e. decision of what is and is not a collision). This technique was then validated by comparing the automatically detected collisions to manually labelled collisions using video analysis of elite and international level rugby players during competition. The validation analysis illustrated that by applying machine learning techniques to accelerometer signal data, it is not only possible to automatically detect and distinguish what is and is not a tackle during competition, but also to do it accurately. The learning grid model yielded very few false positives (i.e. detecting a collision when there was not one) and false negatives (i.e. not detecting a collision when in fact there was one), with very high recall and precision ratings of 0.933 and 0.958 respectively (Kelly et al., 2012). Automatic tackle detection data derived from accelerometers may provide coaches and medical staff with objective data to help develop training, prehabilitation and conditioning programs to reduce the likelihood of collision-related injuries.

Supporting the use of tri-axial accelerometers to assess impact forces in collision-based football codes are investigations that demonstrate the convergent validity of accelerometer derived parameters during training and matches (Boyd et al., 2013; Gastin et al., 2013). During AFL matches, peak GPS and accelerometer data were identified at the point of physical contact (i.e. tackles made and against) via video based coding and subjectively categorised into low, medium and high impact groups. Peak running velocity immediately prior to contact was substantially greater in high intensity tackles (19.5 ± 6.1 kmh^{-1}) compared to medium (13.4 ± 5.8 kmh^{-1}) and low intensity (11.3 ± 5.0 kmh^{-1}) tackles. Peak PlayerLoad^{TM} of high intensity tackles (7.5 ± 1.7 a.u.) was significantly ($p < 0.01$) greater compared to medium (4.9 ± 1.5 a.u.) and low intensity (4.0 ± 1.3 a.u.) tackles. Making intuitive sense, results demonstrated that when compared to tackles of lower intensity, high intensity tackles are significantly ($p < 0.01$) greater in speed of movement immediately prior to physical contact and in the resultant impact acceleration (Gastin et al., 2013). Accelerometers thereby display convergent validity, given increased running velocity immediately prior to contact did in fact lead to increases in Peak PlayerLoad™ at impact. Consequently, practitioners may use GPS receivers with embedded accelerometers to differentiate between tackles of varying intensity or magnitude and aid in the quantification, monitoring and prescription of physical contact loads in football codes.

In AFL training and competition, similar patterns between the number of contact-based events performed by each playing position and low-velocity external loads quantified by accelerometer-derived PlayerLoad™Slow (i.e. PlayerLoad™ at movement speeds below 2 $m.s^{-1}$) provides further justification for the use of accelerometers to quantify contact loads (Boyd et al., 2013). For example, ruckmen displayed the greatest PlayerLoad™Slow of any position, which is in congruence with their involvement in a greater number of contact-related activities compared to other playing positions (ruckmen 173 ± 36, midfielders 119 ± 17, center half-forwards and backs 92 ± 20, small forwards and backs 75 ± 11, and full forwards and backs 71 ± 19) (Dawson et al., 2004). Locomotor loads of AFL training and matches may be estimated by accelerometers, given the strong relationship observed between total running distance and PlayerLoad™ (r = 0.9, Figure 2.8) (Aughey, 2011; Boyd et al., 2013). Accelerometer-derived vector magnitudes may therefore be used as a proxy measure of total running distance covered when GPS methods are unavailable (e.g. within indoor environments). Strong relationships between total distance and PlayerLoad™, accelerometers ability to discriminate between playing positions, playing drills and quantify many frequently occurring, low-velocity movements provided initial evidence to support the use accelerometers to measure external loads of footballers (Boyd et al., 2013).

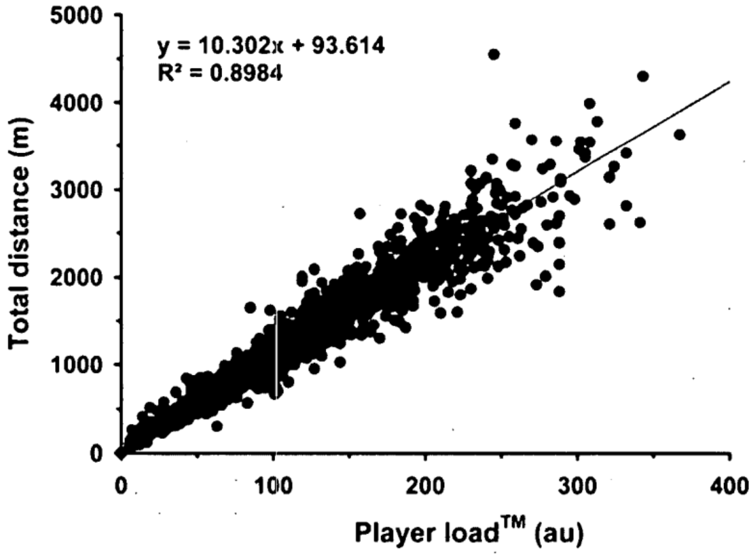

Figure 2.8 The relationship between total distance and PlayerLoad™ in elite AFL players. Reproduced from (Aughey, 2011).

Whilst correlations between total distance and accelerometer derived PlayerLoad™ were promising for applications of accelerometers within team sport, the validity of tri-axial accelerometers worn on the upper body to estimate peak forces during running and change of direction tasks was still unknown. To tackle this gap in knowledge, researchers evaluated the validity of an accelerometer (SPI Pro, ASP00725, GPSports Pty. Ltd., Canberra, Australia) to measure peak vertical and resultant (i.e. tri-axial) force during running and change of direction tasks by comparing values with a criterion in-ground force plate (BP600900, Advanced Mechanical Technology Inc.,Watertown, MA, USA) (Wundersitz et al., 2013). Seventeen participants completed four different running and change of direction tasks (0°, 45°, 90° and 180°) five times each. The peak vertical and resultant acceleration values of each exercise task were then converted to force (via: $F = m \times a$) to compare to the peak ground reaction force raw and smoothed values. The resultant smoothed (10 Hz) and peak vertical raw acceleration data (except 180°) were not significantly different ($p < 0.05$) to the resultant and vertical ground reaction for all running and change of direction tasks. Resultant accelerometer measures displayed no to strong correlations with the ground reaction forces (*r* = 0.0-0.8) and moderate to large measurement errors (CV = 12-24%). Vertical accelerometer measures exhibited small to moderate correlations (*r* = -0.26 to 0.39) and moderate to large measurement errors (CV = 15-21%). Findings illustrated that dynamic movements that occur in multiple planes such as running and change of direction are more accurately measured using resultant (i.e. multiple planes summated) data as opposed to using single axis (e.g. crania-caudal) accelerometer data alone. This is likely due to the body worn accelerometer at the upper back deviating from a 'true' vertical position during many running and change of direction tasks. For example, during high-speed running trials (5-6 $m.s^{-1}$) recreational athletes assumed a more forward-leaning and crouched posture (Keller et al., 1996). Further, during anticipated and unanticipated running and side-step cutting tasks, participants displayed minor lateral trunk orientations outside of the vertical plane of between 5-10% (Houck et al., 2006). Together, peak foot-strike impact forces should be recorded using resultant 10 Hz smoothed accelerometer data to improve measurement accuracy (Wundersitz et al., 2013).

To ascertain the reliability and convergent validity of accelerometer-derived PlayerLoad™ and the individual component planes of PlayerLoad™ for quantifying running at various speeds, forty-four team sport athletes completed two standardised incremental treadmill running tests (7-16 $km.h^{-1}$) seven days apart (Barrett et al., 2014). During the running tests, oxygen uptake, heart rate and tri-axial accelerometer (MinimaxX, Catapult Sports, Scoresby, Victoria) data were measured between the scapulae and at the athlete's center of mass. Accelerometer data from the three individual PlayerLoad™ planes were also assessed (anteroposterior, mediolateral and craniocaudal). PlayerLoad™ and its three individual planes exhibited moderate to high test-retest reliability (ICC = 0.80-0.97, CV = 4.2-15%) at both scapulae and center of mass receiver locations. Interestingly PlayerLoad^{TM} was significantly higher at the center of mass compared to the scapulae (223 ± 43 vs 186 ± 26 a.u.; p = 0.001). Percentage contributions of the individual planes to the vector magnitude PlayerLoad^{TM} were evident between the two accelerometer placements on the body. The contribution of the mediolateral plane (i.e. side-to-side movements) to the total tri-axial PlayerLoad^{TM} were higher at center of mass accelerometer placements when compared to scapulae placement across all running speeds (center of mass = 27% ± 5%, scapulae = 20% ± 4%, p = 0.001). When it came to craniocaudal (i.e. up and down) acceleration contributions to total PlayerLoad^{TM}, center of mass estimates were lower than at the scapulae (center of mass = 50% ± 7%, scapulae = 56% ± 5%; p = 0.001). Correlations between PlayerLoad^{TM} and oxygen uptake and heart rate were nearly perfect within subject between the two standardised running tests (r = 0.92-0.98) demonstrating convergent validity, whilst between-subject correlations were trivial to moderate (r = -0.43 to 0.33). Altogether, PlayerLoad^{TM} displayed moderate to high test-retest reliability and exhibited convergent validity with measures of exercise intensity on an individual basis at both body placements (Barrett et al., 2014). Thus, PlayerLoad^{TM} may be used reliably to examine differences in individual athlete's external load. Yet authors cautioned the use of accelerometers placed at the scapulae for making between-athlete external loading comparisons to identify lower-limb movement patterns due to the influence of individual running styles (e.g. stride rate) on ground-reaction forces. Whilst the convergent validity and reliability of accelerometers was deemed acceptable during incremental running tests at 7-16 km.h^{-1}, the criterion validity of accelerometers to measure peak accelerations at a range of locomotor speeds was still unclear.

To elucidate the validity of accelerometers for measuring peak accelerations during walking, jogging and running, thirty-nine participants wore a trunk-mounted accelerometer that measured 10 peak accelerations per movement (n = 390) whilst running on a treadmill (Wundersitz et al., 2014). To assess the validity of the tri-axial accelerometer, a 12-camera motion analysis system acted as the criterion measure that tracked the position of a retro-reflective marker attached to the accelerometer receiver. Compared to the criterion motion analysis system, the peak raw acceleration values were overestimated by the trunk-worn (housed within a vest between the scapulae) accelerometer ($p = < 0.01$). Filtering the raw peak acceleration values using 8 and 10 Hz cut-off frequencies did however significantly improve the correlations with the criterion measure ($p = < 0.01$). As the magnitude of acceleration increased from walking to jogging to running, the validity of accelerometer recordings when compared to the criterion decreased. In brief, raw peak acceleration data overestimates criterion-referenced values, filtering data improves accuracy and error of peak acceleration estimates increases linearly with increases in locomotor speed.

For player tracking receivers to be capable of providing coaches with an accurate representation of the external load their athlete's complete during training or competition, they must provide valid information on collisions, tackles, jumping, non-linear tasks such as change of direction and many sports-specific movements. To evaluate the validity of accelerometers to measure peak impacts during team sport movements, 76 participants completed a circuit comprised of: walking, jogging, sprinting, change of direction, tackling and jumping; with accelerometer measurements concurrently compared to a criterion 36-camera motion analysis system (Wundersitz et al., 2015a). Peak accelerations per movement were compared using two methods. The first involved pooling the peak accelerations of each movement together and filtering the raw accelerometer data at 13 different cut-off frequencies (6-25 Hz) to identify the optimal accelerometer signal filtering frequency. The second involved using the optimal cut-off filtering frequency discovered using the first method to split the 7 movements (walking, jogging, sprinting, change of direction, tackling, single and double leg jumps) performed (n = 532). Raw and 16-25 Hz filtered accelerometer data significantly overestimated the criterion 36-camera system peak acceleration values, whilst 6 Hz filtering of accelerometer data underestimated peak accelerations of typical team sport movements ($p < 0.007$). Filtering data at 12 Hz yielded the strongest relationship between accelerometer and criterion values (accuracy: -0.01 ± 0.27 g, ES: -0.01, agreement: -0.55 to 0.53 g, precision: 0.27 *g*, and relative error: 5.5% ; $p = 1.00$) (Wundersitz et al., 2015a). Peak accelerations during tackling and jumping were underestimated by the accelerometer, and overestimated during walking, jogging, sprinting and change of direction. During sprinting, jumping and tackling there was lower agreement between accelerometer and criterion values and reduced precision. When filtered at 12 Hz, the accelerometer (100 Hz tri-axial accelerometer; Minimax S4, Catapult Sports, Australia) data displayed acceptable concurrent validity compared to the 36-camera motion analysis system. Findings advocated for the use of accelerometers to measure many movements that frequently occur during team sports.

To thoroughly examine the validity of trunk-worn accelerometers to measure physical collisions in team sports, peak impact acceleration data produced from accelerometers were compared to a criterion 3-dimensional motion analysis system during tackling and bumping (Wundersitz et al., 2015b). Twenty-five semi-elite rugby players wore a tracking receiver with an embedded 100 Hz tri-axial accelerometer (MinimaxX S4, Catapult Sports, Australia). A retroreflective marker was attached to the receiver, with its position measured via a 12-camera motion analysis system (Raptor-E, Motion

Analysis Corp, USA) operating at 500 Hz) during three physical collision tasks (tackle bag, bump pad, and tackle drill; n = 625). The body-worn (i.e. trunk) accelerometer overestimated peak impact accelerations during physical collisions when compared to the criterion motion analysis system (mean bias = 0.6 *g*; $p < 0.01$). When the raw accelerometer data were filtered at 20 Hz, the accelerometers relationship (i.e. accuracy, agreement, precision) with the criterion dramatically improved (mean bias = 0.01 *g*; $p > .05$), signifying improved measurement validity. Peak impact accelerations during the three collision tasks of 3.0 *g* or less (i.e. low impact accelerations) were the most accurately measured by accelerometers when compared to the criterion. Precision of the accelerometer reduced as the magnitude of impact acceleration increased from above 3 *g* to 10+ *g*. The tackle-bag task that involved participants running for 5 meters before tackling a stationary upright tackle bag exhibited the strongest agreement and precision between the accelerometer and motion analysis system of the three collision tasks. Results demonstrated that the MinimaxX S4 accelerometer can accurately measure peak impact accelerations during physical collisions, provided accelerometer data are filtered at a 20 Hz cut-off frequency (Wundersitz et al., 2015b). Consequently, accelerometers may be useful to measure physical collisions during collision-based football codes. However, further investigations were required to test the validity and reliability of accelerometers for the measurement of both dynamic and static movements in more controlled conditions.

In a laboratory controlled environment, the validity and reliability of four SPI-ProX II GPS receivers (GPSports, Canberra, Australia) with embedded accelerometers was evaluated under both dynamic and static conditions (Kelly et al., 2015). Both intra- and inter-receiver reliability was examined via the ability of the SPI-ProX II accelerometer to repeatedly measure peak gravitational accelerations during impact based testing using a purpose-built rotating mechanical device. Validity of the SPI-ProX II that is commonly used in football codes was assessed by comparing acceleration values to a criterion-referenced ADXL345 tri-axial sensor (Analog Devices, Victoria, Australia) during static and dynamic (5-15 Hz) mechanically evoked oscillations. The accelerometer housed within the SPI-ProX II was a BMA150 (Bosch, Germany) tri-axial sensor, that sampled at 100 Hz, with a ± 8 *g* full-scale seismic-acceleration range. The accelerometer operates through a bandwidth of 25 to 1500 Hz and within a temperature range of -40°C to +80°C. In comparison, the criterion referenced and certified calibrated ADXL345 accelerometer operated over a much larger bandwidth of 0.1 to 3000 Hz, with the same sampling frequency (100 Hz), 8 *g* full-scale seismic-acceleration range and similar operating temperature range of -40°C to +85°C. During reliability testing of the SPI-ProX II accelerometer, impacts of the mechanically rotating device were delivered at 82 milliseconds to peak force to approximate the epoch of a tackle in contact based field sports (Pain et al., 2008). To ensure the vibration platform (Galileo Sport Control 0544, Novotec Medical, Germany) used for dynamic validity testing of both accelerometers was reliable; the platform was previously tested over 40 oscillations using an 8 Hz frequency. The 8 Hz frequency was selected as it approximates high-frequency, non-contact human locomotion (Chen et al., 2005). Both the rotating mechanical device and the vibration platform displayed good reliability (CV of 2.3% and 1.7% respectively).

The SPI-ProX II accelerometers exhibited excellent intra-receiver reliability (CV = 1.9-2.2%), with no significant ($p < 0.05$) differences observed between the four accelerometer receivers. The SPI-ProX II accelerometer consistently measured peak gravitational acceleration between 7.9 and 8.5 *g* across 10 repeated impacts, with no significant differences ($p = 0.5$) observed between receivers, indicating excellent inter-receiver reliability. However, validity testing exposed poor static and dynamic validity of the SPI-ProX II accelerometer when compared to the criterion-referenced accelerometer. During static validity testing, there were very large differences (ES > 3.4) between receivers, equating to 28 to 31%. In addition, the four SPI-ProX II accelerometers recorded less than ± 1 *g* when rotated through all degrees of freedom (vector magnitude range: 0.69 to 0.74 *g*). This is concerning given accelerometers should read close to 1 *g* when stationary due to the gravitational acceleration of earth being equivalent to $9.8 m.s^{-2}$, corresponding to 1 *g*. For comparison, the criterion referenced accelerometer recorded static vector magnitudes of between 0.988 to 1.006 *g*, evidently much closer to 1 *g*. Dynamic validity testing revealed large underestimations of peak acceleration across all 5 to 15 Hz vibration platform oscillating frequencies, with differences compared to the criterion ranging from 32 to 35%. Altogether, the SPI-ProX II accelerometers proved reliable but not valid during laboratory controlled static and dynamic tasks, underestimating the magnitude of acceleration by approximately 30%. Similar large error differences of > 20% have been reported between GPSports SPI Pro accelerometers compared to a force-plate criterion measure for measurement of impacts during jumping and landing tasks (Tran et al., 2010). Accelerometer receiver placement and receiver vibration occurring due to movement within the harness were thought to have attributed to the poor accuracy of the raw data (Tran et al., 2010). Equivocal accelerometer validity findings across several investigations provoked researchers to further question whether body-worn accelerometers provide accurate estimates of whole-body mechanical loading.

Accelerometers embedded within GPS receivers are often used in professional team sports to estimate the external forces acting on player's bodies (Barrett et al., 2016; Boyd et al., 2013; Colby et al., 2014). The receivers are worn on the dorsal part of the upper trunk between the scapulae within an elastic vest and thereby quantify the acceleration of a player's upper trunk segment. Using trunk accelerometry to estimate the external forces acting on the human body is based on Newton's second law of motion [Force (whole-body) = mass (whole-body) × acceleration (whole-body)] and the assumption that body-worn accelerometers are able to measure whole-body acceleration (Nedergaard et al., 2016). As GPS embedded accelerometers measure trunk accelerations, the external forces measured are not necessarily whole-body related [i.e. Force (trunk) = mass (trunk) × acceleration (trunk)]. Yet if segmental accelerations measured from the trunk relate to whole-body accelerations then it may be feasible to estimate external forces athletes endure on the field during training and competition.

The relationship between body-worn accelerometer location and whole-body mechanical loading during running and change of direction tasks that frequently occur in team sports has been investigated in recent years (Nedergaard et al., 2016). Forward running and anticipated 45° and 90° side-cuts at approach speeds of 2, 3, 4 and 5 $m.s^{-1}$ were completed in randomised order four times each, by twenty male team sport athletes. Whole-body accelerations, biomechanically expressed as Center of Mass (CoM) accelerations were measured via ground reaction forces collected from one foot-ground-contact using a Kistler force plateform (9287C, Kistler Instruments Ltd., Winterthur, Switzerland) embedded in the floor, that sampled at 3000 Hz. Segmental accelerations were measured by a commercially available GPS receiver (MinimaxX S4, Catapult Sports, Scoresby, Australia) with an embedded accelerometer (KXP94, Kionex, Inc., Ithaca, NY, USA). The commercially available accelerometer sampled at 100 Hz, with an output range of ± 13 *g* and was placed on the upper trunk between the scapulae within a tightly fitting elastic vest in accordance with manufacturer's recommendations. In addition, three higher specification tri-axial accelerometers (518, DTS accelerometer, Noraxon Inc., Scottsdale, USA) with an 1000 Hz sampling frequency and 24 *g* output range were affixed to three body segments: 1. directly fixed to the posterior aspect of the commercially available accelerometer on the trunk, 2. dorsal aspect of the pelvis and 3. shaft of the tibia. The relationships between mechanical load variables (peak acceleration, loading rate and impulse) calculated via both CoM as well as segmental accelerations were examined by regression analysis. Statistical parametric mapping was used to investigate the relationship between peak CoM vs. segmental acceleration profiles during whole foot-ground-contact on the force plate.

Weak associations were reported for the mechanical load variables regardless of the accelerometer location and exercise task (r^2 peak acceleration: 0.08-0.55, r^2 loading rate: 0.27-0.59 and r^2 impulse: 0.02-0.59). The segmental accelerations (i.e. trunk, pelvis and tibia) consistently overestimated the whole-body mechanical load variables (peak acceleration, loading rate and impulse). The commercial and criterion accelerometer placement at the trunk yielded the strongest predictions of whole-body peak acceleration and impulse, whilst accelerometer placement at the pelvis and tibia were the best predictors of loading rate regardless of the running or cutting task. Somewhat surprisingly, the addition of multiple accelerometer location data to the regression model analysis only slightly improved the relationship with the CoM acceleration mechanical loading variables. Peak segmental acceleration data were most highly correlated to whole-body mechanical loading during the 10-50% (i.e. initial phase) of foot-ground-contact (Nedergaard et al., 2016).

The consistent overestimation of peak whole-body loading from body-worn accelerometers can simply be explained via the differences in acceleration of the individual body segments (tibia, pelvis and trunk) being much greater than CoM (whole-body) accelerations. Similar findings were observed between peak resultant accelerations from a trunk mounted accelerometer and resultant peak ground reaction forces produced during running and change of direction tasks at comparable speeds (Wundersitz et al., 2013). These findings make intuitive sense, as body-worn accelerometers can only measure the acceleration of the body segment they are attached to. Therefore the common assumption of a strong linear relationship (based on Newton's second law of motion) between segmental (often trunk) acceleration and whole-body (CoM) acceleration is flawed and not sufficient to accurately quantify the linked multi-segment dynamics of the human body during team sports in the field. Future investigators should explore the application of multi-segment accelerometer models to more accurately estimate the mechanical loading team sport athletes experience (Nedergaard et al., 2016).

Lending support for the common current practice of positioning the GPS-embedded accelerometers on the trunk was that peak segmental accelerations measured at the trunk displayed the strongest relationship to the peak whole-body (CoM) acceleration (Nedergaard et al., 2016). This may be due to the attenuation of the accelerometer signal as it travels up through the body from the ground (Hamill et al., 1995), and/or because the trunk represents a much larger proportion of the body (50%) when compared to the pelvis (14%) and tibia (4.7%) (Dempster, 1955). Results demonstrate that whilst trunk accelerometry data displays only weak correlations to whole-body loading variables during team sport movements; it is likely practitioners' best bet to estimate whole-body mechanical loading in the field. Practitioners should reflect on the weak to moderate linear relationships between body-worn accelerometry and whole-body mechanical loading when interpreting accelerometer data in the field.

To understand whether body-worn accelerometer derived PlayerLoad^{TM} (exercise volume measure) and PlayerLoad^{TM}.min^{-1} (exercise intensity measure) are reliable, task- and player-specific measures that demonstrate convergent validity, fifteen male participants completed a football match simulation protocol twice (Barreira et al., 2017). The modified soccer-specific simulation protocol (mSAFT^{90}) (Raja Azidin et al., 2015) comprised of four multidirectional actions common in football (i.e. jog, side cut, stride and sprint) that participants completed whilst wearing a trunk mounted GPS receiver (Viper model, Statsports Technologies, USA) embedded with a tri-axial 100 Hz accelerometer (ADXL 326, Analog Devices, Norwood, USA). Both PlayerLoad^{TM} and PlayerLoad^{TM}.min^{-1} displayed moderate to high reliability (ICC = 0.81 - 0.95) across multidirectional football tasks of varying intensity from jogging to maximal sprinting. Moderate to high accelerometer derived PlayerLoad^{TM} reliability has been observed across several studies using a range of protocols, including: soccer-specific SAFT^{90} (Barrett et al., 2016), treadmill running (Barrett et al., 2014), mechanical (Kelly et al., 2015; Nicolella et al., 2018) and/or field based testing (Boyd et al., 2011). Between participant PlayerLoad^{TM} and PlayerLoad^{TM}.min^{-1} variation during the soccer-specific mSAFT^{90} protocol (CV = 15-25%) was reported to be more related to an individual's locomotor skills than their body composition (Barreira et al., 2017). This finding was surprising given individual characteristics such as body mass are known to influence ground reaction forces (Derrick et al., 2000) and thereby increased participant body mass should have resulted in increased PlayerLoad^{TM} recordings from the accelerometers if they were to display convergent validity. Although the accelerometers did display some level of convergent validity in that PlayerLoad^{TM}.min^{-1} was related to the running velocity of the exercise tasks.

Recent mechanical testing of commercially available GPS receivers with integrated accelerometers has found excellent intra-receiver reliability, mixed inter-receiver reliability (i.e. very large to nearly perfect intraclass correlation coefficients: 0.77 - 1.0) depending on the magnitude and direction of the applied motion and poor validity of a commonly used accelerometer (Nicolella et al., 2018). Nineteen accelerometers (Catapult OptimEye S5, Catapult Sports, Team Sport 5.0, Melbourne, Australia) sampling at 100 Hz were mounted to an aluminium bracket that was bolted to an electrodynamic shaker table (Unholtz Dickie 20K) and subjected to a series of oscillations, varying in direction and magnitude. The electrodynamic shaker table oscillated the fixed accelerometers in three directions (forward-back, side-to-side and up-down) at various peak acceleration levels (0.1 *g*, 0.5 *g*, 1.0 *g*, and 3.0 *g*) for 30 seconds each. This process was repeated five times, culminating in 60 trials per accelerometer receiver, for a total of 1140 peak acceleration measurements across the nineteen receivers. To examine the criterion validity of the nineteen commercially available receivers, a calibrated single-axis reference accelerometer (J353B31, PCB Piezoelectronics, Depew, NY) was also mounted to the shaker table. To further assess the validity of the Catapult accelerometer PlayerLoad™ recordings, investigators calculated PlayerLoad™ independently from the raw acceleration data using Catapult's publicly available Cartesian algorithm for direct comparison.

Similar to previous mechanical testing protocols (Boyd et al., 2011; Kelly et al., 2015), the commercially available accelerometers exhibited excellent intra-receiver reliability, with intra-class correlation coefficients ranging from 0.8 (very large, 95% CI: 0.6 ± 0.9) to 1.0 (nearly perfect, 95% CI: 0.99 ± 1.0). Conversely, inter-receiver reliability displayed mixed results, with small (ES = 0.5, 95% CI: 0.3 ± 0.7) to large (ES = 1.2, 95% CI: 1.1 ± 1.3) effect size differences between accelerometer receivers for mean peak accelerations and PlayerLoad™ for each direction and level of acceleration. Small (ES = 0.4, 95% CI: 0.2 ± 0.5) to moderate (ES = 1.2, 95% CI: 1.0 ± 1.3) effect size differences were observed between the Catapult OptimEye S5 and the criterion accelerometer peak acceleration recordings in all three directions and all four acceleration magnitudes. The Catapult reported PlayerLoad™ was consistently 15% lower than the vector magnitude calculated via the use of raw acceleration data and the Cartesian formula. This suggests that the manufacturer further manipulates PlayerLoad™ beyond the Cartesian algorithm described (Nicolella et al., 2018), presumably via the division of PlayerLoad™ by a "scaling factor" that is unfortunately not transparently described for commercial users. Due to the excellent intra-receiver yet mixed inter-receiver reliability findings, practitioners may confidently use OptimEye S5 receivers to monitor and prescribe player movement across time provided they use the same receiver. Comparison of different player's movement profiles with different accelerometer receivers should be exercised with caution due to the highly variable (trivial to extreme) inter-receiver reliability. Given these results, authors stressed the importance of establishing industry wide standards for periodically evaluating the reliability and validity of wearable technology so that practitioners may reliably, confidently and interchangeable use receivers in practice (Nicolella et al., 2018).

2.5.9 Global Positioning Systems & Accelerometers as Player Tracking Tools

Position, velocity and distance can be derived via GPS (Larsson, 2003). Subsequently, change in velocity (acceleration and deceleration) may be calculated (Varley et al., 2012b) and potentially used in combination with velocity-based events to estimate the energy cost of exercise (metabolic power) (Di Prampero et al., 2005). Whilst GPS athlete tracking data can be of great value to practitioners, it has reduced validity and reliability for quantifying rapid changes of direction (Rawstorn et al., 2014) and velocity (Akenhead et al., 2014; Jennings et al., 2010), estimating metabolic power (Buchheit et al., 2015) and for assessing short duration, high-velocity tasks that frequently occur in team sports (Coutts et al., 2010a; Jennings et al., 2010). Movements that incur little horizontal displacement (e.g., collisions, jumping, tackles and many sport-specific movements) are also likely to be underestimated by GPS (Boyd et al., 2013).

Accelerometers overcome some of the limitations of GPS and have been used to quantify athlete external load (Boyd et al., 2013) and energy expenditure (Walker et al., 2015) during training and competition, with PlayerLoad™ moderating the recovery response of footballers (Rowell et al., 2016). Accelerometers are reliable in laboratory (Kelly et al., 2015) and field settings (Boyd et al., 2011), can accurately detect physical contact (Hulin et al., 2017; Kelly et al., 2012; Wundersitz et al., 2015b), jumping and landing (Spangler et al., 2018; Tran et al., 2010) sport-specific movements (McNamara et al., 2015) and alterations in movement strategies, efficiency or kinematic changes (Barrett et al., 2016; Cormack et al., 2013). Unlike GPS, accelerometers can also operate within indoor environments, providing greater utility (Aughey, 2011).

Accelerometers have a much higher data sampling rate when compared to GPS (100 Hz vs. 10 Hz respectively) allowing the detection of small and rapid movements. Subsequently, accelerometers are better able to detect changes in how locomotion is produced and temporal changes in player movement (Cormack et al., 2013). For instance, in a study comparing the relative contribution of each accelerometer axis (x, y, z) to overall PlayerLoad™, AFL players who were classified as fatigued pre-match had a reduction in the contribution of the vertical axis during competition (Cormack et al., 2013). Reduced vertical axis contribution during locomotor and sport-specific movements when fatigued may reflect a reduced capacity to accelerate or sprint, vertical stiffness (Girard et al., 2011) or relate to player's adopting running patterns characterised by increased knee flexion (McMahon et al., 1987). Accelerometers may therefore detect alterations in technique or movement strategies and offer a more sensitive measure of transient fatigue in athletes than absolute external load measures (Cormack et al., 2008).

Variations in accelerometer-derived external load parameters can differentiate between playing positions (Boyd et al., 2013; Cormack et al., 2014), contact vs non-contact small-sided games (Boyd et al., 2013) and between training and matches in AFL (Boyd et al., 2013). For instance, PlayerLoad™Slow (that removes activity above 2 $m \cdot s^{-1}$ from PlayerLoad™) was able to identify that whilst midfield players consistently had the highest match PlayerLoad™ of any position, ruckmen had higher PlayerLoad™Slow than all other positions. This result suggested that PlayerLoad™Slow may provide different information about low-speed activity (e.g. grappling, contact). Most football codes are characterised by contact and comprise many low-speed movements that likely impose different physical stress than running locomotion alone. External load may be severely underestimated if these low-speed activities are not quantified and monitored. Accelerometer-derived external load information has the potential to inform recovery and training practices. Whilst there are many promising applications of commercially available accelerometers to measure human movement, they too have limitations that ought to be acknowledged.

Poor accelerometer validity observed in both mechanical (Kelly et al., 2015; Nicolella et al., 2018) and laboratory (Nedergaard et al., 2016) settings may result from many sources, such as accelerometer hardware, body placement (Barrett et al., 2014; Nedergaard et al., 2016), harnessing apparatus, and data processing procedures (Tran et al., 2010; Wundersitz et al., 2014). Reduced accelerometer accuracy during static testing may result from errors produced via incorrect axis orientation, high cross-axis sensitivity and poor stability (Hansson et al., 2001). Processing of the raw accelerometer data also has large ramifications on the accuracy and thereby validity of the data. For instance, smoothed (e.g. fourth order, zero lag, dual pass, Butterworth digital filter with a 20 Hz cut-off frequency) accelerometer data reduced error compared to a force plate criterion measure (CV = 11-22%) versus raw accelerometer data estimates (CV = 17-31%) (Tran et al., 2010). Selection of an appropriate bandwidth filter to reduce non-physiological noise derived from accelerometer drift errors or vibrations is imperative for valid data (Chen et al., 2005). Narrow bandwidth filters may not record all data from physical activity (Welk, 2005), whilst exclusion of signal fluctuations above set cut-off frequencies can substantially alter the original signal (Bisseling et al., 2006). For example and as mentioned previously, 16-25 Hz bandwidth filtered accelerometer data significantly overestimated criterion 36-camera system peak acceleration values, whilst 6 Hz filtering of accelerometer data underestimated peak accelerations of typical team sport movements (p <0.007) (Wundersitz et al., 2015a). Accelerometers also display some insensitivity to quantifying low-intensity movements, while recording non-linear data at higher-intensity movements (Hendelman et al., 2000b).

The ability of accelerometers to accurately estimate whole-body accelerations when attached to various body locations has also been questioned (Nedergaard et al., 2016). Accelerometer-derived PlayerLoad™ measured from the player's trunk is commonly used in practice to estimate the total external load during training or competition. Whilst trunk-mounted accelerometer data displayed only weak correlations to whole-body loading variables during team sport movements; it is likely practitioners best bet to estimate whole-body mechanical loading in the field, with greater associations than pelvis or tibia placement (Nedergaard et al., 2016). Practitioners should reflect on the strengths and limitations of any technology, understanding its validity, reliability and sensitivity to best interpret and use the data to inform decisions that influence the training process. Altogether, accelerometers provide valuable additive external load information to GPS that may aid practitioners in more accurately quantifying, monitoring and prescribing movement in collision-based team sports. The following section will discuss activity profile data analysis techniques, with a focus on techniques used to quantify the most intense (i.e. peak) periods of football competition using wearable technology.

2.6 Football Activity Profile Analyses

Tracking athlete field position and activity profiles can be done via an array of optical systems, global and local positioning systems. These tracking systems can give practitioners valuable information on player position, distance, velocity, distances covered across a range of velocities and changes in velocity, thus acceleration. Absolute activity profile measures such as distance travelled give practitioners information about the volume of physical work completed. Absolute measures such as distance are often better expressed as distance relative to time spent exercising, to better understand the intensity of a match or training session (Varley et al., 2013b). For instance, GPS technology revealed the total distance travelled during international cricket competition was 13,400 m (Petersen et al., 2010), whilst an elite AFL player ran 12,939 m (Coutts et al., 2010b), suggestive that cricket is the more "demanding" sport (Aughey, 2011). In contrast, when the distance covered is expressed per minute of match time, the AFL player nearly doubled the relative distance (109 $m.min^{-1}$) or "average intensity" of the cricketer (63 $m.min^{-1}$). This finding stresses the importance of using relative measures when trying to make activity profile comparisons between sports that have different match durations (see Table 2.1). In an activity profile comparison of the football codes, AFL players covered the greatest relative distances (129 ± 17 $m.min^{-1}$) compared to rugby league (97 ± 16 $m.min^{-1}$) and soccer players (104 ± 10 $m.min^{-1}$) (ES: 1.0-2.8) (Varley et al., 2013b). Expressing absolute measures relative to the time spent on the field is incredibly important when evaluating the activity profile of full-match players versus substitutes, the intensity of matches versus training or comparing the intensity of players being rotated on and off the field of play (Aughey, 2010). However, fluctuations in running intensity are expected during football competition given their stochastic nature and whole-match averages such as relative distances are not sensitive enough to detect these subtle activity profile fluctuations (Delaney et al., 2016d; Furlan et al., 2015; Jones et al., 2015). Simply assessing the average intensity of a competition hides the worst-case scenarios that players will be exposed to in matches and need to be physically and psychologically conditioned for. This has ramifications for training prescription, as drills based on whole-match averages will inevitably underprepare athletes for the most intense periods of competition (Delaney et al., 2016d). Despite the majority of team sport competition being spent at submaximal intensity, high intensity periods of competition are often aligned with key events that determine the match outcome (Faude et al., 2012; Gabbett et al., 2016). Therefore, conditioning football players for the most intense (peak) periods of competition is imperative to match outcome (winning or losing). Understanding athlete movement during the most intense periods of team sport matches may assist in the development and prescription of training that is more representative of competition and inform match-day substitution decisions (Delaney et al., 2015). The following sections will discuss methods for identifying and quantifying fluctuations in player movement during competition, with an emphasis on identifying peak periods of football competition and declines in movement thereafter using wearable technology.

2.6.1 Identifying & Quantifying Peak Periods of Football Competition

Several studies have investigated temporal fluctuations in player movement during football competition to harvest insights on pacing strategies, relationships to skilled performance and fatigue (Aughey, 2010; Bradley et al., 2013b; Carling et al., 2011; Furlan et al., 2015; Jones et al., 2015; Lacome et al., 2017; Mohr et al., 2003). The nature of football movement is very complex and temporal oscillations during competition relates to a host of contextual factors. Earlier in this chapter, a simple framework for conceptualising the numerous factors (not all encompassing) that may influence the intermittent and chaotic nature of football movement was created based upon review of the literature (Table 2.2). Four clear factor categories emerged from our review: 1. Sport-, 2. Team- & Match-, 3. Individual- and 4. Environmental-related contextual factors. The plethora of factors within these four broad categories may help to explain the chaotic and undulating nature of football match movement. Improved understanding of the links between these factors and resultant player movement and pacing strategies during match-play may aid representative training design and inform real time substitution or rotation decisions. Several factors that may influence player movement during the most intense periods of match-play will be explored further in Chapter 5. The ensuing sections will provide a synthesis of literature investigating fluctuations in player movement during various football competitions, as there are many similarities in how these factors may influence movement between codes.

A recent systematic review identified the methodologies and wearable micro-technology variables used to determine the peak "match demands" or intensities and summarised the peak periods of competition across the football codes (Whitehead et al., 2018b). Twenty-seven studies met eligibility criteria and six football codes were reported on: rugby league (n = 7), rugby union (n = 5), rugby sevens (n = 4), soccer (n = 6), Australian Football (n = 2) and Gaelic Football (n = 3). Three peak period identification methodologies were identified: 1. Rolling/moving average analysis, 2. Pre-defined/segmental analysis and 3. Longest period ball in play analysis. In pre-defined or segmental analysis, a time period of interest is chosen (e.g. 5 minutes) and then the match data is split up into the chosen time period accordingly following the zero minute mark when the match commences (e.g. 0-5, 5-10, 10-15 minutes, etc.). Identification of the peak period of competition is then simply a matter of selecting the period with the highest value for any movement measure/s of interest (Whitehead et al., 2018b).

During professional soccer, high-intensity (>18 km.h^{-1}) running distance quantified by computerised tracking systems was significantly lower (35-45%; $p < 0.05$) in the last 15 minutes of matches compared to the first 15 minutes, irrespective of playing position or competition level (Mohr et al., 2003). Immediately following the peak 5 minute pre-defined period of high-intensity running, high-intensity distance declined by 12% in the ensuing 5 minutes compared to the match average. Similarly, during professional soccer both total and high-speed running (> 14.4 km.h^{-1}) distances were greater in the first versus second half of matches ($p < 0.001$) and in the first versus final 15 minutes of play ($p < 0.05$) (Carling et al., 2011). Moreover, high-intensity (≥ 14.4 km.h^{-1}) running distance was significantly greater in the first versus last 5 minutes of matches, and during the peak 5 minutes versus the 5 minute period immediately following and match average ($p < 0.05$). Likewise, post the most intense 5 minute period of soccer competition, computerised tracking quantified an 8% decline in high-intensity (≥ 14.4

km.h^{-1}) running (p < 0.05) when compared to the match average (ES = 0.2) (Bradley et al., 2013b).

Using computerised video-based player tracking, the relationship between end-game and transient changes in match running activity and whether these periods were concomitantly associated with declines in skilled performance was evaluated in senior international rugby union (Lacome et al., 2017). Both rugby forwards and backs displayed small to moderate reductions (-42%, ± 10 to -21%, ± 7) in high-speed (≥ 18 km.h^{-1}) running distance in the final 5 and 10 minutes of matches compared to the average across all other 5 and 10 minute pre-defined periods (Lacome et al., 2017). Although only small concomitant changes (-18%, ± 51 to 13%, ± 41) in skill-related performance were observed. Drastic reductions in high-speed running distances were observed for both forwards and backs from the peak 5-minute period to the following 5-minute period (-50% ± 21 and -49% ± 16, respectively). Large reductions in high-intensity running distances covered following the peak 5 minute period of competition however did not translate to reduced skilled performance (number of passes). Trivial differences were observed between the number of passes completed in the period following the peak when compared to the mean number of passes completed across all other 5 minute epochs (backs: -8% ± 58, forwards: -11% ± 74) (Lacome et al., 2017).

Temporal movement fluctuations between match-halves and between pre-defined 10-minute periods of matches have been investigated using wearable 10 Hz GPS receivers (MinimaxX v.4.0, Catapult Sports, Melbourne, Australia) with embedded 100 Hz accelerometers during professional rugby competition (Jones et al., 2015). Temporal analysis of match-halves revealed that PlayerLoad^{TM}.min^{-1}, cruising (2.7-3.8 m.s^{-1}) and striding (3.8-5.0 m.s^{-1}) relative distances significantly (p < 0.05) declined from first to second halves (PlayerLoad^{TM}.min^{-1}: 6.9 vs 6.5 a.u., cruising distance: 11.8 vs. 10.6

m.min^{-1}, striding distance: 7.4 vs. 6.5 m.min^{-1}). Several measures of both low- and high-intensity movement and acceleration/deceleration progressively declined during match-halves and across successive 10 minute periods ($p < 0.05$), indicative of accumulative fatigue (Jones et al., 2015). Whilst the number of repeated high-intensity efforts (Gabbett et al., 2012b) and contacts did not significantly change between any 10-minute period during the first half, both measures significantly declined during the 50-60, 60-70 and 70-80 minute periods when compared to the first 10 minutes of the second half (40-50 minute period). High-intensity running (5.0-5.5 m.s^{-1}) and sprinting (> 5.6 m.s^{-1}) distances covered during the final 10 minutes of matches were not significantly different to the average distance covered across all other 10 minute match periods. Similarly, no substantial declines were observed between high-intensity running (5.0-6.7 m.s^{-1}) and sprinting (> 6.7 m.s^{-1}) distances covered during progressive 10 minute periods across 80 minute professional rugby matches (Roberts et al., 2008). In contrast, rugby players covered greater total distances during the first 10 minutes of matches when compared to the 50-60 and 70-80 minute match periods in the second half. Taken together, findings suggest that rugby players may preserve their energy by completing less low-intensity activity as matches progress so that they may recover to a greater extent in order to complete higher-intensity tasks when called upon to do so, with similar findings observed during AFL matches (Coutts et al., 2010b). Reduced low-intensity activity as rugby matches progress may be characterised by an inability of players to maintain defensive position or run supporting lines in attack (Roberts et al., 2008). Quantifying team, position and individual fluctuations in football activity profile during competition using wearable technology and temporal analyses may inform preparation of conditioning and rehabilitation drills, tactical decisions (e.g. substitutions/rotations) and the application of match-day strategies to enhance physical performance (e.g. half-time re-warm up) (Jones et al., 2015). Whilst temporal analyses of football match quarters, halves or pre-defined periods have provided valuable information on match activity profile fluctuations, the sensitivity of these data analyses techniques to accurately identify these fluctuations (e.g. peak movement periods) has been questioned (Varley et al., 2012a).

The most intense or peak periods of football competition do not often fall completely within a pre-defined period of time and therefore these methods underestimate the most intense periods of match-play and overestimate subsequent periods of activity (Cunningham et al., 2018; Ferraday et al., 2020; Varley et al., 2012a). During elite soccer competition the peak periods of high-velocity running distance were identified using either pre-defined (distance covered in 5 minutes at every 5 minute time point) or rolling time periods (distance covered in 5 minutes from every time point). Rolling or moving average methods involve analysing raw instantaneous data from the receiver used. For example, GPS receiver data are commonly sampled at 10 Hz (i.e. ten times per second) and accelerometer data typically at 100 Hz (i.e. one hundred times per second). To identify the peak periods of competition using a moving average approach, one must select a duration of interest (e.g. 5 minutes), with that window of time then moved across every second of the competition, collecting a moving average from every single time point. For example, using a one-minute window that equates to 600 samples (60 s with ten samples per second using 10 Hz GPS), the moving average would be applied to a player's match data file as follows: 0-600, 1-601, 2-602, 3-603 etc., to identify the one-minute peak measure/s of interest (Whitehead et al., 2018b). During professional soccer competition, peak high-velocity running distance was underestimated by up to 25% using pre-defined time period analysis, with the subsequent period distances overestimated by up to 31% when compared to rolling time period analysis. When the distance decline in high-velocity running between the peak and following period were examined, there was up to a 52% greater reduction in running performance using rolling vs. pre-defined periods (Varley et al., 2012a). Likewise during international rugby competition, both high-speed running (>5 $m.s^{-1}$) and relative distance ($m.min^{-1}$) were consistently underestimated by pre-defined compared to rolling period analyses of 60-300 seconds (Cunningham et al., 2018). Pre-defined epoch analyses on average underestimated relative distances covered by ~11% and high-speed running by up to ~ 20% compared to rolling epoch analyses, with the greatest underestimations occurring using the 60 second epoch (95% compatibility interval, high-speed running: -6.1 to -4.7 $m.min^{-1}$, relative distance: -18.5 to -16.4 $m.min^{-1}$) (Cunningham et al., 2018). Similarly in English Championship soccer matches, pre-defined epoch analyses of 60-600 seconds underestimated peak movement intensities of competition when compared to rolling epoch analyses for both total distance (∼ 7-10%) and high-speed (∼ 12-25%) distance, irrespective of playing position (Ferraday et al., 2020). Therefore, it is recommended that researchers and practitioners use rolling/moving time period analyses when trying to accurately identify and quantify the peak periods of football competition (Varley et al., 2012a).

Duration- and position-specific player movement differences have been observed during the most intense periods of match-play using rolling epoch analysis across various football codes including: rugby league (Delaney et al., 2015), rugby union (Delaney et al., 2016d), Australian Rules Football (Delaney et al., 2017a) and soccer (Delaney et al., 2017b). These investigations amongst others have provided valuable insights into the highly intermittent nature of team sport movement and highlighted that rolling time-motion analyses may assist practitioners in the design and prescription of training that is more representative and specific to competition. The following sections will elaborate on findings from investigations using wearable GPS and accelerometer technology and rolling epoch analyses to identify, quantify and predict the most intense periods of football code competition and periods thereafter. Whilst the focus of this thesis is on rugby (rugby union), considerable insights can be gleaned from examining methodologies, analysis techniques and findings reported from other football codes, warranting further discussion.

2.6.1.1 Predefined vs. rolling epoch analysis

The first investigation to explore the most intense periods of football competition and periods thereafter discovered that pre-defined epoch analysis substantially underestimated peak 5 minute high-velocity running distance and overestimated the distance in the subsequent period compared to rolling epoch analysis (Varley et al., 2012a). The peak 5 minute high velocity (≥ 4.17 $m.s^{-1}$) running distances of 19 elite soccer players pooled across 11 matches and all positions was 177 ± 91 $m.min^{-1}$ and 166 ± 43 $m.min^{-1}$ in the first and second match-halves respectively using rolling epoch analysis. In contrast, using pre-defined period analysis the peak periods were 142 ± 24 $m.min^{-1}$ and 138 ± 41 $m.min^{-1}$ respectively, representing a ~ 20-25% underestimation (ES range: 0.6-0.7). The 5 minute period immediately following the most intense period of competition saw drastic reductions in movement intensity using both analysis techniques (pre-defined: 72-80 $m.min^{-1}$ vs. rolling: 52-64 $m.min^{-1}$). However, as pre-defined period analysis underestimated the peak intensity of soccer competition by ~ 20-25% it subsequently overestimated the following period by ~ 24-31%. Consequently, the overall average decline in movement between the most intense 5-minute period of elite soccer matches and the subsequent period was underestimated by 113 $m.min^{-1}$ or ~ 52% when using pre-defined analysis. This seminal study paved the way for subsequent research attempting to quantify, characterise and understand the most intense periods of football competition and periods thereafter, for the primary purpose of match-specific training prescription and monitoring.

2.6.1.2 Rolling epoch analysis

Wearable GPS receivers have been used to investigate the temporal fluctuations in running intensity within and between match-halves and to establish the level of agreement between external load measures used to identify movement fluctuations within elite rugby sevens competition (Furlan et al., 2015). During twenty-one World Sevens Series matches, 12 elite rugby sevens players wore trunk positioned 5 Hz (interpolated to 15 Hz) GPS receivers (Spi HPU, GPSport Systems, Canberra, Australia) to quantify their activity profiles. Both relative distance (kinematic, $m.min^{-1}$) and metabolic power (energetic, $W.kg^{-1}$) measures were calculated via velocity-time curves and used to evaluate between match-half fluctuations. Rolling average 2 minute periods were used to calculate the peak intensity of competition and compare peak relative distance to metabolic power. The pre- and post-peak adjacent 2 minute periods were also examined to identify fluctuations in intensity. Both relative distance and metabolic power displayed small to moderate declines from the first to second half (9% and 6%, respectively). The peak 2 minute intensities of the respective measures (130 $m.min^{-1}$ and 13 $W.kg^{-1}$) were understandably significantly greater than the match average (94 $m.min^{-1}$ and 10 $W.kg^{-1}$) and the pre- and post-peak periods ($p < 0.001$). Relative distance underestimated ($p < 0.001$) the intensity of the peak 2 minute period when compared with metabolic power [mean bias = 16%, 95% Limits of Agreement (LoA) = 16% ± 6]. The point in time during competition when the peak 2 minute intensity period occurred and was identified differed between the two measures (mean bias = 21 seconds, LoA ± 212 seconds). Findings illustrated that running intensity fluctuates both within and between match-halves and that the external load measure utilised influences both the magnitude and the temporal identification of the peak periods (Furlan et al., 2015).

The first study to investigate the position and duration specific running intensities of professional football using several rolling average epochs found that the peak periods of rugby league match-play are considerably more intense than previously reported (Delaney et al., 2015). Utilising 15 Hz GPS receivers (SPI HPU, GPSports, Canberra, Australia), 32 professional rugby league players were tracked across a competitive season. Maximum relative distance values were calculated via rolling average analysis of the velocity-time curve using durations of 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 minutes for each player, during each match. Pairwise comparisons between rolling-average durations revealed significant ($p < 0.05$) relative distance differences between all durations, with the exception of the 9- vs. 10-minute comparison. As the length of the rolling epoch decreased, the peak relative distance substantially increased relative to the longest epoch duration (10 minutes). There were moderate to large differences displayed between the 1- and 2-minute peak relative distances and all other rolling average duration peak intensities ($p < 0.05$), yet the magnitude of these differences decreased as the rolling average duration increased. Significant positional differences were observed across positional groups and rolling averages, although these differences were small and would not be substantial enough to warrant the prescription of different intensities. However, fullbacks produced greater peak relative distances than both middle and edge forwards across 1- and 2-minute rolling durations (ES: 0.8-1.2, $p < 0.05$). Further, the running intensity of fullbacks was greater than that of middle forwards and outside backs for durations of 3 minutes or greater (ES: 1.1-1.4, $p < 0.05$) (Delaney et al., 2015).

Creation of duration and position specific peak intensity of competition frameworks provides valuable information to coaches for the planning, prescription and monitoring of specific training drills, such as small-sided games (Delaney et al., 2015). For example, as fullbacks were the only position to display substantially greater running intensity than any other position, training prescription attempting to replicate the peak periods of match-play should reflect this. It was recommended that coaches periodically prescribe specific game-based methodologies such as small-sided games to better replicate the reactive and multidirectional nature of rugby league (Delaney et al., 2015). Coaches may manipulate the drills field size, number of players, rules and verbal encouragement to achieve the desired training intensity obtained via rolling-epoch analysis of competition. Whilst this study provided valuable frameworks for the prescription and monitoring of position and duration specific running speeds, the energetic and acceleration profile of professional rugby league athletes was still unknown.

To investigate the energetic cost of running and acceleration efforts during the most intense periods of rugby league competition, 37 professionals wore trunk-mounted 15 Hz GPS receivers (SPI HPU, GPSports, Canberra, Australia) to track player movement over two competitive seasons (Delaney et al., 2016a). Peak values for relative distance, average acceleration/deceleration and metabolic power were calculated using rolling/moving average durations from 1-10 minutes for each positional group. Relative distance is a commonly used measure in time-motion analyses, yet it only considers speed of movement and pays no regard to the energetic cost of accelerated running. Therefore, relative distance was used to compare a speed-based measure against acceleration-centric measures of metabolic power and average acceleration/deceleration. Metabolic power considers the energetic cost of accelerated running on flat terrain to be energetically analogous to running on an equivalent uphill slope at a constant speed (Di Prampero et al., 2005). Instantaneous metabolic power output ($W.kg^{-1}$) of an individual may subsequently be calculated if acceleration and velocity are known (Di Prampero et al., 2005; Osgnach et al., 2010). The average acceleration/deceleration measure turned all acceleration and decelerations values positive to create an indicator of the total acceleration requirements of an athlete, independent of velocity (Delaney et al., 2016a).

To evaluate the effect of rolling average duration on running intensities, a magnitude-based approach (Hopkins, 2007a) was used to compare the 1-9 minute averages with the 10 minute average, for each of the three outcome measures. A multilevel mixed-effects statistical model was used to examine the effect of playing position for each rolling epoch duration, with individual comparisons made using a magnitude-based decision approach (Hopkins, 2007a). Large differences (ES: 1.2-1.9) in peak relative distance and metabolic power were reported between the 10 minute rolling period and all durations less than 5 minutes. The positional groups of fullbacks, halves and hookers covered greater peak relative distances when compared to outside backs, edge forwards and middle forwards for all rolling average durations between 2-10 minutes. Hookers and halves had greater peak acceleration/deceleration profiles versus fullbacks, middle forwards and outside backs. Somewhat in agreement, the other acceleratory measure metabolic power was also greatest in hookers, halves and fullbacks compared to middle forwards and outside backs. Findings shed further light on position and duration specific movement profiles of rugby league athletes during the most intense periods of match-play, whilst emphasising the importance and need to accurately quantify acceleratory movements to better prescribe and monitor specific training drills (Delaney et al., 2016a).

The most intense periods of rugby (rugby union) competition were first quantified by Delaney and colleagues (Delaney et al., 2016d), employing an identical framework to describe the duration and position specific intensities as their previous investigation in rugby league (Delaney et al., 2016a). Peak running intensity increased as the duration of the rolling average epoch decreased. Small to moderate (ES = 0.3-1.0) increases in peak relative distance and average acceleration/deceleration were observed for outside backs, half-backs and loose forwards compared to the tight 5 group (props, hooker, locks) across all 1-10 minute durations. Outside backs and half-backs produced moderately greater metabolic power when compared to the tight 5 (ES = 0.9-1.0). Half-backs covered the greatest relative distances and produced the highest metabolic power outputs of any positional group, yet had similar average acceleration/deceleration profiles to outside backs and loose forwards during the most intense periods of rugby competition (Delaney et al., 2016d). The study provided a novel framework to describe the peak running profiles of elite rugby players during competition by position, which were substantially greater than previously reported whole-period rugby match averages.

2.6.1.3 Longest periods of ball in play

The longest periods of ball in play during matches may be used to identify and quantify activity profile worst-case scenarios of football competition (Reardon et al., 2017). Thirty-nine professional rugby player's movement was tracked during 6 games in the European Rugby Championship and 11 games in the Guinness Pro12 league using 10 Hz GPS receivers (10 Hz S5, Catapult Sports, Scoresby, VIC, Australia). The ERC was considered the higher standard of rugby competition, as teams qualify for the ERC by finishing in a high ladder position in domestic leagues such as Pro12. Ball in play duration was defined as the time the ball entered play until it went dead or until the play was stopped by the referee. The longest period of ball in play was then compared between positional groups (regardless of competition level) and between levels of competition for each position using separate multivariate analyses of variance. Two expert video analysts determined the number of collisions during the "worst-case scenario" period of competition for each player. Collision count reflected the count of all tackles, scrums, mauls, carriers into contact and positive impact rucks. The longest period of ball in play averaged across the four positional groups was 156 seconds (range 152-161 seconds). Similar to rolling average epoch analysis, using the longest period of ball in play time to identify the peak running intensity periods of competition yielded substantially greater running intensities than the use of whole-match averages (average relative distance: 117 $m.min^{-1}$ vs. 68 $m.min^{-1}$ respectively).

During the worst-case scenarios of competition, compared to forwards the backs covered greater total distances (318 m vs. 289 m), completed more high-speed running (11 $m.min^{-1}$ vs. 6 $m.min^{-1}$) and achieved higher maximum velocities. Outside backs recorded the highest maximal velocity (6.8 $m.s^{-1}$) and covered the most high-speed running distance (14 $m.min^{-1}$). Within the worst-case scenarios of competition forward positions are characterised by more collisions and low-speed running than backs. For instance, tight five and back row forwards engaged in substantially more collisions than inside and outside backs (0.7 & 0.9 $collisions.min^{-1}$ vs. 0.3 & 0.4 $collisions.min^{-1}$ respectively). These results are consistent with previous global activity profile analyses of rugby competition, with forwards engaging in more high-intensity collision-based movements and backs completing more high-intensity running and sprinting (Duthie et al., 2006; Quarrie et al., 2013).

Within the longest periods of ball in play (~ 156 seconds) the majority of activity is low-intensity in nature with intermittent bursts of high-intensity running and collision-based movements. The vast majority of "worst-case scenario" comparisons between levels of rugby competition yielded non-significant differences. Despite the lack of statistical significance, there were some inter-competition differences during that may be of practical significance to coaching staff. For example, outside backs covered substantially greater high-speed running distances during Pro12 competition than in the European Rugby Championship (16 $m.min^{-1}$ vs. 9.7 $m.min^{-1}$). The use of longest ball in play time analysis to identify the "worst-case scenario" of competition, individualised speed zones and video analysis to help accurately quantity collision events were study novelties that have contributed to our understanding of the most intense periods of rugby competition.

2.6.1.4 Factors influencing peak and post peak football intensties

Whilst not the central focus of the investigation, Kempton and colleagues examined an array of physical, possession and collision variables during the peak 5 minutes of rugby league competition and compared these values to the subsequent 5 minutes and the 5 minute match average values using GPS and rolling epoch analysis (Kempton et al., 2015b). Movement data were obtained from 18 rugby league players during 38 games throughout two National Rugby League seasons using 5 Hz GPS receivers (SPI-Pro, GPSports, Canberra, Australia). Physical movement measures included: total distance (m), high-speed running (> 14.4 $km.h^{-1}$) distance, high-power (> 20 $W.kg^{-1}$) distances, average metabolic power ($W.kg^{-1}$) and collisions (n). The most physically intense 5 minutes of competition was significantly greater than both the subsequent (ES range: 1.7-3.5) and mean (ES range: 2.0-4.3) 5 minute periods for total distance, high-speed distance, high-power distance and metabolic power (p < 0.001). However, no significant differences were observed for the frequency of collisions between the peak, subsequent and mean 5 minute periods.

Contextual analysis of possession status revealed on average across all matches and positional groups that rugby league players spent more time in defence (121 seconds) than in attack (106 seconds) during the peak 5 minute period of competition. The remaining 74 seconds of the 5 minute (300 seconds) peak rolling average period (study stated 301 s presumably via rounding values) were spent with the ball out of play. Results of this investigation highlighted the drastic temporal changes in activity profile that occur during rugby league competition, possibly due to fatigue and/or several contextual factors (Kempton et al., 2015b). Quantifying the inevitable decline in physical movement directly after the most intense periods of match-play (explored further in Chapter 6) has implications for match-day substitution/rotation decisions and prescribing active recovery training intensities between maximal efforts. Analysis of the number of collisions alongside locomotor variables during the most intense periods of match-play whilst providing contextual information such as time in attack or defence may aid the design of training drills aiming to replicate the worst-case scenarios of competition.

The most intense periods of football competition likely differ between playing standards, from juniors to semi-professional to professional standards, culminating in international competitions such as World Cups. To examine the peak running relative distances ($m.min^{-1}$) of both club and international youth under-16 rugby league players during matches, 10 Hz GPS receivers (Optimeye S5, Catapult Sports, Melbourne, Victoria) were used, with rolling epoch analysis of 10, 30, 60- to 600 seconds conducted (Whitehead et al., 2018a). International youth forwards covered very likely (95-100%) greater (than the smallest worthwhile change: 0.2 × between subject standard deviation) (Hopkins, 2007a) peak relative distances than club level forwards for durations of 60, 180 and 600 seconds. Although for the backs, club level players produced greater peak relative distances during the 10 and 60 second epochs, with unclear effects for other time periods. The shorter (i.e. 10 and 30 second) rolling epoch durations used than previous rugby league studies of between 1-10 minutes (Delaney et al., 2016a; Delaney et al., 2015) may aid the design of conditioning drills with repeated very high-intensity bouts. The longer duration epoch (e.g. 10 minutes) peak running intensities may be used to monitor the intensity of training drills that aim to replicate match intensity whilst concurrently focussing on technical and tactical elements (i.e. tactical periodization) (Whitehead et al., 2018a). Differences in the peak relative distances covered between youth competition level were position dependent, with greater relative distances covered at club level for backs but at the international level for the forwards. Improved understanding of the peak intensities of different levels of competition (investigated in Chapter 5) provides coaches with indicators of how the activity profile change when players progress to higher levels of competition.

During the World Rugby under 20 Cup tournament 62 player's match running and skilled performance was monitored using GPS to examine the potential effects of congested playing schedule and high exposure time (Carling et al., 2017). Of the 62 players across two teams that were monitored with 10 Hz GPS receivers (Viper 2™, Statsports Technologies™, Newry, Northern Ireland), 36 (57%) participated in 4 matches and 23 (37%) in all 5 matches of the tournament. High-metabolic load distance (distance covered > 5.5 $m.s^{-1}$ + accelerating > 2 $m.s^{-2}$) (Osgnach et al., 2010) was identified and quantified using 5 minute rolling average analysis for each player, positional group (forwards and backs) and match. The peak 5 minute high metabolic power distances covered were likely (75-95%) to very likely (95-99%) higher to a moderate extent in the final match compared to matches 1 and 2 of the tournament for both backs and forwards (ES range: 0.6-1.2). Across all five-tournament matches, the backs produced on average 11.5 $m.min^{-1}$ higher metabolic power distances during the peak 5 minutes when compared to the forwards. Findings suggest that backs have greater metabolic loads than forwards do during the peak 5-minutes of matches and that the two teams as a whole coped physically well with the intensive tournament match scheduling. Sufficient recovery time between matches (4-5 days), effective monitoring and recovery practices and the highly developed physical qualities of players of international standards were offered as potential explanations as to why the players peak 5-minute high-metabolic load distance was not reduced as the tournament progressed (Carling et al., 2017). Novel insights into the peak metabolic loads produced by international youth rugby players across an intensified tournament schedule may have implications for team selection during such tournaments, or aid subsequent training and recovery monitoring and prescription practices.

The maximum running intensities of rugby player's during matches are duration and position specific for both youth (Read et al., 2018b) and senior (Delaney et al., 2016d) competitions. In youth rugby, running intensity for consecutive rolling epoch durations (e.g. 15 vs. 30 s, 30 s vs. 60 s) decreased from a small to very large extent as duration increased (ES range: 0.5 – 2.8). Maximum running intensity as measured by the peak relative distance was lower for forwards than backs across all 15-600 second durations (ES ± 90% CI: −0.7 ± 0.2 to −1.2 ± 0.2) (Read et al., 2018b). When breaking the large positional forward and back packs into sub-positional groups, youth front row forwards and scrum half backs peak relative distances were substantially different to other sub-positional groups. The novelty of this research when compared to previous research was that authors chose the rolling durations of 30 seconds and 2.5 minutes to correspond with the mean and maximum ball in-play cycles for academy rugby (33 and 149 seconds respectively) (Read et al., 2018a), providing ecological validity for the use of these durations to monitor and prescribe training intensity.

The physical activity profile of players is only of importance if physical prowess improves a player's ability to execute their technical and tactical roles effectively to help their team win. The effect of intense periods of competition on physical and technical performance of elite AFL athletes was investigated and compared between more and less experienced players (Black et al., 2016). Twenty-four professional AFL players from one team were monitored across 13 matches using 10 Hz GPS receivers (S4, Catapult Sports, Melbourne, Australia). Player distances covered during competition were segmented into total distance, low-speed activity (0-2.78 $m.s^{-1}$), moderate-speed running (2.79-4.14 $m.s^{-1}$) and high-speed running ($\geq$ 4.15 $m.s^{-1}$) distances. The number and quality of game-specific technical skills were manually coded using match broadcast video footage. The quality of player kicks, handballs, ball handling and attempted tackles were classified using a standardised 5-point Likert scale (1 = poor; 5 = excellent) that was developed in consultation with football analysis professionals and an expert coach. Players were classified as 'experienced' if they had played at the elite level for five or more years (n=14), whilst players with four or less years experience were classified as 'less experienced' (n = 10). Peak physical and technical skill performance were analysed using a 3 minute rolling average approach (Varley et al., 2012a), as 6 minutes was the minimum amount of time between player rotations at the football club. To investigate whether the peak 3 minutes of competition influenced physical and/or technical performance, the same measures were compared to the 3 minutes immediately subsequent to the peak and the mean of all the other 3 minute match periods (not including the peak and subsequent period) for each individual. Any players that were substituted off the field during the 3-minute period following their peak running period were excluded from analysis.

Following the most intense 3 minute period of competition, the experienced players ran greater distances at high-speeds in match quarters two (ES ± 90% CI = 0.42 ± 0.30) and three (0.38 ± 0.33) than less experienced players. Relative to their less experienced counterparts, experienced players performed more skill involvements during the second (0.42 ± 0.33) and fourth quarter peak 3 minute bouts of exercise intensity (0.40 ± 0.30). Experienced players also performed a greater number of skilled involvements directly after the most intense 3 minutes of match quarters one (0.49 ± 0.29) and three (0.33 ± 0.20), when compared to less experienced players. Less experienced elite AFL players displayed greater reductions in both physical and technical performance following the most intense passages of competition. Findings suggested that it may be pertinent to regularly, progressively and periodically expose less experienced players to the worst-case scenarios of competition so that they are better able to maintain high physical intensities and gain possession of the football during and following these very high-intensity periods (Black et al., 2016). Further, authors proposed that coaches consider rotating less experienced players on and off the field more frequently in an effort to prevent declines in exercise intensity following the most intense passages of play (Black et al., 2016). Future research should explore the relationships between the most intense passages of play, key technical performance indicators and match outcome (win/loss). Player movement post the most intense passages of competition is likely dependent on the duration of the peak period analysed, competition level, playing position, time on field, time of match the peak occurs alongside a host of other variables, which will be examined in Chapter 6.

Identifying whether the most intense periods of competition are influenced by score line, opponent rank and substitutes may assist coaches to contextualise the activity profile of players. During an international rugby sevens tournament, 17 professional players wore GPS receivers to measure both full-match and peak 1-minute periods of activity. Measures of relative distance, high-speed running distance (4.17 - 10.0 $m.s^{-1}$), and the occurrence of maximal accelerations ($\geq$ 2.78 $m.s^{-2}$) were assessed via a 1-minute rolling average. The first 1-minute period at the start of each match-half for distance per count was recorded in absolute terms (m/count). Peak relative distance and high-speed running distance declined between professional rugby sevens match-halves, regardless of the score line or opponent ranking (Murray et al., 2015). Close match score lines (i.e. 7 points or less difference between team scores) at halftime were associated with greater high-speed running distance in the first minute of both the first and second match-halves when compared to a winning (i.e. reference team was winning by more than 7 points) half-time score line. In matches played against higher vs. lower ranked opposition, players covered moderately (26%; 90% CL = 6, 49) greater total distances during the first minute of the first match-half. Late substitutions (i.e. players on the field < 4 minutes) had greater relative distance, high-speed running and accelerations than players who played a full match but the peak 1-minute periods for all three measures were lower than for early substitutes (came on field in the first 4 minutes of the second half) and full match players. Altogether, findings demonstrated that match score line, opposition rank and timing of substitutions can influence both the average and peak intensity of rugby sevens competition (Murray et al., 2015). Rugby sevens players are likely to perform more running when the score line is close and when competing against higher-ranked opposition teams. Given peak periods of activity were reduced in the second compared to the first match-half regardless of score line or opposition, there is need to condition players appropriately to attenuate these declines. These findings have the potential to inform team selection, substitution decisions and half-time strategies. Further research should continue to investigate the influence of a range of contextual factors (see Table 2.2 for a comprehensive framework) on the most intense periods of competition, across several epoch durations and positional groups.

2.6.1.5 Match-to-match peak intensity variability

It is important for coaches to understand the typical match-to-match variation of player activity profiles to accurately assess and confidently monitor differences or changes in the physical output and performance of players. Forty-five elite female soccer players were monitored with GPS and accelerometry to examine the match-to match variation of running across a whole-match and during and post the most intense periods of international soccer matches (Trewin et al., 2018). Player activity profile data were collected via the use of 10 Hz GPS receivers (Minimax S4, Catapult Sports, Australia) with an embedded accelerometer. A rolling 5 minute epoch was used to identify the most intense 5 minutes of matches as well as the subsequent 5 minutes, for players who played the entire 90 minutes of matches (172 files). The activity profile measures used to assess the whole-match and peak running intensity of each playing position during competition were: relative distance (m.min^{-1}), high-speed (> 4.58 m.s^{-1}) running per minute and counts per minute, sprint efforts (> 5.55 m.s^{-1}) per minute, maximal acceleration counts (> 2.26 m.s^{-2}) per minute and PlayerLoad^{TM} (a.u.) per minute. Match-to-match variation of these measures were calculated via the co-efficient of variation and 90% compatibility limits. The smallest worthwhile difference (SWD) of each measure was calculated as 0.2 of the raw between-player standard deviation, prior to log transformation. The SWD may be used to assess 'true' differences in player activity, observed as a change greater than the SWD (Hopkins et al., 2009). Peak 5 minute movement periods were no more variable than full-match activity profile analyses, underlining that rolling epoch analyses are able to identify the worst-case scenarios of competition. For instance, the peak 5 minute relative distance match-to-match variation of 7.2% (90% CL: 6.5, 8.0) was similar to the whole-match relative distance match-to-match variation of 6.8% (90% CL: 6.2, 7.6). Relative distance displayed the smallest variation of any measure. Movement after the most intense 5 minutes of competition was substantially more variable than during peak running periods or across the whole match, limiting the efficacy of post peak analyses for identifying transient fatigue. For example, the amount of high-speed running per minute completed after the peak 5 minutes was extremely variable (CV = 143%, SWD = 13%). The greater frequency and reduced variability of maximal acceleration count per minute (CV = 17%) when compared to high-speed running and sprint efforts per minute (CV = 34% and 56% respectively) demonstrates accelerations improved stability and suitability for tracking player movement from match to match. Further, acceleration per minute may also be a more sensitive measure to detect worthwhile changes in activity profile or performance between matches, with a smaller SWD (3.8%) compared to high-speed based metrics (6.4-9.2%). PlayerLoad™ per minute was also a more stable external load measure from match-to-match during both peak periods (CV = 14%, 90% CL: 13, 15) and whole matches (CV = 14%, 90% CL: 13, 16) than high-speed running per minute and counts (CV range: 31-33%) and sprinting counts per minute (CV = 53%, 90% CL: 46, 60). Authors suggested that PlayerLoad™ could be used with relative certainty, although only within player comparisons should be considered. Positional differences in match-to-match variation of the measures was evident, with center backs exhibiting the largest variation in high-speed movements (CV = 41-65%).

The novel examination of match-to-match variation of commonly used GPS and accelerometer-derived measures during and post the peak intensities of elite female soccer competition (Trewin et al., 2018) provided insights that can help coaches to assess and interpret changes in player activity profiles within and between matches. The match-to-match and SWD data for each movement measure can be used by practitioners to monitor often small yet important changes in movement within individuals (or grouped into positions), between matches that may inform training prescription and subsequent monitoring practices. Future research should examine the match-to-match variation of peak movement periods and periods thereafter using a range of rolling epoch durations across the football codes. Likewise the within individual, between match and between individual, within match reliability and sensitivity (i.e. signal: noise) of GPS and accelerometer-derived measures during the peak periods of match-play is poorly understood. Improved understanding of the reliability and sensitivity of wearable technology measures during peak periods of competition (Investigated in Chapters 3 and 4) would help coaches to interpret and use player movement data to influence the training process.

2.6.1.7 Modelling peak intensity periods of Football

Human beings are principally nonlinear organisms that rely on complex interactions between many physiological feedback systems (Higgins, 2002; Katz et al., 1994). Several developments in our understanding of nonlinear systems have discovered that fractal (power law) relationships may be the rule, not the exception in physiological systems (Goldberger et al., 1990; Katz et al., 1994). Human senses perceive the intensity of sound, light, taste, smell, pain and pressure stimuli with power law characteristics (Lodge, 1981). The allometric relationship (Thompson et al., 1917) between a mammal's mass and its resting metabolic rate (White et al., 2005) and human

DNA sequences (Oliver et al., 1993) have also been characterised via power law. Power law relationships have been reported to characterise a wide array of natural phenomena in ecology, biology, physical and social sciences (White et al., 2008). Power law describes a nonlinear yet dependent relationship between two variables (x and y), where one variable (y) changes as a fixed power (exponent) of another (x). The parameters of power law relationships are used to make inferences about processes underlying phenomena, to test theoretical or mechanistic models, and to estimate and predict patterns or processes that are outside of and beyond the scope of observed experimental data (White et al., 2008).

The first development and use of power law to mathematically explain the relationship between running time (*T*) and distance (*D*) covered for human athletic events and horse races was in 1906 (equation 1) (Kennelly, 1906). Equation 1 represents the power law relationship between running time and distance, with *c* and *n* being positive constants:

$$T = cD^n \tag{1}$$

Kennelly stated, "…the records (i.e. speeds of racing humans and horses) align themselves closely to a simple mathematical relation" that "could hardly be expected from the performances of different animals at different times and in different parts of the world" (Kennelly, 1906). Kennelly termed the power law relationship between running times and distances "an approximate law of fatigue" that may be used for practical purposes given the "satisfactorily small limits of deviation" from the mathematical model. Since Kennelly's seminal work, several others (Henry, 1955; Katz et al., 1999; Katz et al., 1994; Lietzke, 1954; Riegel, 1981) have used this power law model due to its goodness of fit to human running records of various distances with R^2 values (coefficients of determination) very close to 1. However, even linear regression analysis of running and swimming times and distances yielded similarly strong R^2

values of close to 1 (Katz et al., 1999). Despite strong correlations, linear regression models overestimated 100, 200 and 400 m men's world record running times by 209%, 73% and 13% respectively. Conversely, power law analysis underestimated 200 and 400 m times by ~6%, whilst 1000, 1500, 1600, 2000 m running times were consistently overestimated by only ~3% (Katz et al., 1999). Further, the world record running times for distances of 100 to 10,000 m are scattered about the power law regression lines in a pattern that remained consistent for 70 years from 1925 to 1995. Thus, power law regression values display smaller standard errors of the estimate when compared to linear regression models for such purposes, illustrating improved goodness of fit and model accuracy (Katz et al., 1999).

Aerobic and anaerobic contributions to energy expenditure during exercise have been proposed to fit a power function, likely underpinning the excellent fit of running performance times over a wide array of distances, and moderating errors of the power law model estimates (Katz et al., 1999). A.V. Hill, an exercise physiology pioneer stated (1926, p. 98) "Some of the most consistent physiological data available are contained, not in books on physiology, not even in books on medicine, but in the world' s records for running different horizontal distances' (Hill, 1926). Hill proposed that the relationship between a runner's power output (P_T) and the total duration (T) of a race, can be described by a hyperbolic function:

$$P_T = (A/T) + R \tag{2}$$

Where A and R symbolize the capacity of anaerobic metabolism and the rate of energy produced from aerobic metabolism respectively (Lloyd, 1966; Péronnet et al., 1989). Incorporating human metabolic physiology parameters into running time-distance or power-duration equations extended on initial models (Kennelly, 1906), improving their accuracy. Further modification of the hyperbolic model initially developed by Lloyd

(Lloyd, 1966) based upon Hill's observations (see equation 2) yielded average absolute error between predicted and actual Olympic Games running times of 0.86% for distances of 100 to 10,000 m (Ward-Smith, 1985). However, original hyperbolic models (Lloyd, 1966; Ward-Smith, 1985) incorrectly assumed mean aerobic power could be sustained indefinitely, whereas it progressively declines as running distances increase beyond ~3000 m (Péronnet et al., 1987). By accounting for progressive reductions of aerobic power output with increasing running time, model accuracy improved with an average absolute prediction error of 0.73% when estimating world record race times over a wide range of events (60 m to marathon distances) (Péronnet et al., 1989).

Power law (García-Manso et al., 2012; Katz et al., 1994; Kennelly, 1906), exponential decay (Weyand et al., 2006), and hyperbolic models (Monod et al., 1965; Péronnet et al., 1989; Ward-Smith, 1985), which included critical power models and derivatives (Hill, 1993; Skiba et al., 2014) have attempted to achieve 'good fit' to physical performance data with reasonable approximation of underlying physiology. The critical power (CP) model has been popularised in the last ~30 years, particular in cycling and is based on a hyperbolic relationship between power output and the time that the power output can be sustained (Hill, 1993). Critical power signifies the boundary between steady-state and non-steady-state exercise and has been proposed to be a more meaningful measure of aerobic fitness than the lactate threshold and maximal oxygen uptake (Vanhatalo et al., 2011). The physiological fatigue mechanisms underpinning the power-duration relationship have been segmented into four exercise intensity domains: 1. Moderate intensity domain (below the lactate threshold), 2. Heavy intensity domain (above lactate threshold but below critical power), 3. Severe intensity domain (above critical power) and 4. Volitional exhaustion (above $\dot{V}O_2max$) (Burnley et al., 2016). The intensity domain of the exercise dictates the type and degree of fatigue experienced (Burnley et al., 2016). Whilst various non-linear mathematical models have been utilised to describe and predict the power-duration relationship of individual sports (e.g. running, cycling, swimming), there is limited comparative literature examining power-duration relationships in team sports. Non-linear models do have a theoretical basis for practical application in team sports such as soccer and rugby (Vanhatalo et al., 2011), with for example modifications of the critical power model for intermittent exercise contexts (Morton et al., 2004).

Power law analysis has been recently applied in professional soccer (Delaney et al., 2017b; Lacome et al., 2018) and in rugby league (Duthie et al., 2017) to quantify peak intensities and the rate of peak exercise intensity decline as a function of time during competition (Delaney et al., 2017b) and training (Lacome et al., 2018). Power law analysis has also been used to assess youth soccer (Duthie et al., 2018) by age and position and evaluate the relationship between physical performance tests and peak intensities achieved during rugby league competition (Duthie et al., 2017). Power law may be practically applied in team sports to improve match specific exercise intensity prescription and monitoring for any given exercise duration, using specific game-based methodologies, such as small-sided games (SSG) (Delaney et al., 2017b; Lacome et al., 2018).

Table 2.4 Football code power law intercept comparisons (i.e. 1-minute peak intensities).

Football Code	Authors	Measure	Positional Intercept Range
Rugby League	(Duthie et al., 2017)	Mean speed	171-195 $m.min^{-1}$
		Metabolic power	17-20 $W.kg^{-1}$
Soccer	(Delaney et al., 2017b)	Mean speed	173-196 $m.min^{-1}$
		Metabolic power	16-18 $W.kg^{-1}$
Soccer	(Lacome et al., 2018)	Mean speed	147-176 $m.min^{-1}$
		Metabolic power	Not reported
Soccer Youth Under 15-17	(Duthie et al., 2018)	Mean speed	182-194 $m.min^{-1}$
		Metabolic power	24-26 $W.kg^{-1}$

Using wearable Global Positioning Systems (GPS) and rolling average epoch analysis (Varley et al., 2012a) to quantify peak intensities of professional soccer competition, speed- and acceleration-based measures exhibited almost perfect linear declines with increasing exercise durations of 1-10 minutes when log-transformed (r = 0.97-0.98), displaying power law characteristics (Delaney et al., 2017b). Likewise, power law log-log plots have been able to accurately estimate exercise intensity-duration relationships (r = 0.94-1.0) across three exercise measures (total distance, high-speed distance and mechanical work) between professional soccer matches and SSGs (Lacome et al., 2018). However, no team sport study to date has examined the standard errors of power law regression model estimates. Improved understanding of model errors (examined in Chapter 7) may enhance or reduce confidence and use of power law for estimating/modelling match-specific exercise intensities for any given training drill duration.

Rates of decline in running intensity as a function of time were similar between professional soccer playing positions, with trivial to small differences observed (Delaney et al., 2017b). Similarly in youth soccer, there were no substantial differences between playing levels in the decline in running intensity as exercise duration increased (Duthie et al., 2018). In contrast, exercise intensity differences between professional soccer matches and SSG training were highly playing position and SSG type (4v4, 6v6, 8v8 and 10v10) dependent, irrespective of rolling average duration (Lacome et al., 2018). Further, in professional rugby league there were large negative correlations between a player's physical qualities (maximum speed and relative squat strength) and the rate of decline in running speed and metabolic power during competition (Duthie et al., 2017). Rates of peak intensity decline as a function of exercise duration have yet to be examined with power law models incorporating rolling epoch durations of less than 1 minute. No study to date has investigated team sport peak intensity-duration power law characteristics using accelerometer and match-half data. Lastly, whether the power law relationship can accurately predict/model exercise intensities as a function of time in both elite and sub-elite rugby union (rugby) that have higher collision and stoppage frequencies, limiting "free running" time compared to other football codes is still unknown. The purpose of Chapter 7 was to establish whether power law models could accurately model the peak intensities of rugby competition as a function of time.

2.6.1.8 Peak intensity periods of Football: Summary & Gaps in Knowledge

Duration- and/or position-specific player movement differences have been observed during the most intense periods of match-play across various football codes including: rugby league (Delaney et al., 2015; Whitehead et al., 2018a), rugby (Delaney et al., 2016d; Reardon et al., 2017), rugby sevens (Furlan et al., 2015), Australian Rules Football (Delaney et al., 2017a), soccer (Delaney et al., 2017b) and Gaelic football (Malone et al., 2017b). These investigations amongst others have provided valuable insights into the highly intermittent nature of team sport movement and highlighted that rolling time-motion analyses may assist practitioners in the design, prescription and monitoring of training that is more representative and specific to competition. Further applications of these investigations included informing: match-day substitution/rotation decisions, half-time re warm up strategies, recovery practices and team selection. However, there are still many gaps in scientific knowledge when it comes to quantifying and characterising the peak intensities of team sport competition. For example, the sensitivity, reliability and convergent validity of wearable player tracking systems for quantifying peak intensities of team sport competition is not known, limiting a practitioner's ability to interpret and use such data to inform practice (see Chapter 4). There is also a scarcity of research using inertial sensor (e.g. accelerometer) technology for quantifying peak periods of team sport competition, which is surprising given the reduced accuracy of GPS for quantifying high-velocity and acceleratory movements that frequently occur in team sports (Boyd et al., 2013; Jennings et al., 2010; Rawstorn et al., 2014). In a recent systematic review investigating the use of microtechnology to quantify the peak match demands of football codes (Whitehead et al., 2018b), only 2 of the 27 studies that met author's eligibility criteria used accelerometer-derived metrics such as PlayerLoad™ or BodyLoad™, whilst GPS-derived relative distance was reported in 63% of studies. Other poorly understood phenomena that will be examined throughout this thesis include: quantifying activity profiles post peak periods of competition (Chapter 6), quantifying peak player intensities over very short durations (< 1 minute), quantifying peak movement intensity between match-halves and between levels of competition within the same football code (rugby). Characteristics of the most intense periods of rugby competition such as the time of the match they occur, within-season trends and whether time on field influences player peak movement intensity will also harvest innovative findings (Chapter 5). Finally, this thesis will explore the use and accuracy of power law modelling to model professional rugby match intensity as a function of time (Chapter 7).

CHAPTER 3: STUDY 1 - QUANTIFYING IMPORTANT DIFFERENCES IN ATHLETE MOVEMENT DURING COLLISION-BASED TEAM SPORTS: ACCELEROMETERS OUTPERFORM GLOBAL POSITIONING SYSTEMS

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3.1 Introduction

Collision-based team sports such as rugby union are characterised by engaging in, or evading physical contact. Alike many team sports, rugby union is stochastic in nature with the majority of match activity performed at low intensities, punctuated by short periods of high-intensity activity (Duthie et al., 2003). Global Positioning Systems (GPS) are able to calculate and record data on player position, time and velocity (Larsson, 2003). However, GPS has reduced validity and reliability when assessing short duration, high-speed straight line running and rapid changes of direction or velocity that commonly occur during team sport competitions (Coutts et al., 2010a; Jennings et al., 2010). Whether GPS can adequately quantify movements that incur little horizontal displacement (e.g., collisions, tackles) and sport-specific movements even with multiple constellation systems that increases measurement accuracy (Malone et al., 2017a) is questionable (Boyd et al., 2013). Commercially available piezoelectric tri-axial accelerometers embedded within GPS receivers are valid and reliable in laboratory and field settings (Boyd et al., 2011) and are able to accurately detect individual contact events (Gabbett et al., 2010), sport-specific movements (McNamara et al., 2015) and changes in how locomotion is produced (Cormack et al., 2013). Accelerometers may quantify and account for a greater proportion of an athlete's total physical movement in collision-based team sports compared to GPS technology (Boyd et al., 2013). Accelerometers may therefore be more effective in detecting small but meaningful differences in athlete activity profiles during both training and matches.

Valid and reliable quantification of athletic movement via wearable technology is important for sporting practitioners as it provides objective data to inform decision making around: training prescription, player readiness to play, injury risk and player interchange decisions, amongst other emerging applications. The quality of decisions made by practitioners on a daily basis relies on valid and reliable objective data from technologies, measures and analysis methods that are sensitive enough to detect differences in activity within and between players in order to glean useful information. The now widespread adoption of GPS with integrated inertial sensor technology in elite team sports is testament to its perceived worth and impact on player and team preparation and performance. These receivers can capture over 250 physical movement metrics. Given the tsunami of movement metrics or variables to choose from, it is important that practitioners use those that are valid, reliable and sensitive whilst primarily considering each variable's potential utility to influence the training program.

In a recent meta-analysis (Akenhead et al., 2016), acceleration, total distance, high-speed running distance and estimated metabolic power were ranked as the most important variables in the eyes of elite football practitioners. Expressing player movement variables per minute of match time spent on the field as opposed to an absolute total (e.g., completing 100 $m.min^{-1}$ vs 8000 m during an 80 minute match) allows for quantification of movement intensity that may then be used to help guide training prescription (Aughey, 2011). However, if team sport training is prescribed relative to the average intensity of an entire match (e.g., 80-100 $m.min^{-1}$) players will likely be under-prepared for the most intense periods of match-play (e.g., 172 $m.min^{-1}$) (Delaney et al., 2015). Despite the majority of collision-based team sport competition being spent at submaximal intensity, high intensity activities are often aligned with key events that determine the match outcome (win/loss). For example, in rugby league approximately 56% of 2083 repeated high intensity efforts occurred within 5 minutes of either scoring or defending a try during 21 semi-professional matches across 11 teams (Gabbett et al., 2016). These findings have lead to growing interest in using wearable technology to quantify the most intense periods of match-play. The most intense periods of a match do not often fall completely within a pre-defined period of time and therefore these analysis methods may underestimate the most intense periods of match-play and overestimate subsequent periods of activity (Varley et al., 2012a). It is recommended that practitioners and researchers use rolling average epochs (epochs from every time point) as opposed to pre-defined epochs when attempting to accurately quantify the most intense periods of competition as well as fluctuations in activity across a match (Varley et al., 2012a). Given the aforementioned information, the three selected variables of maximum mean movement in the present investigation were: mean speed ($m.min^{-1}$, GPS derived), metabolic power (Metabolic power, GPS derived) and

Playerload™ (accelerometer derived) using a rolling average duration of 600-s, chosen as it is a commonly used training drill duration when attempting to replicate the most intense periods of team sport match-play.

Accelerometers may quantify and account for a greater proportion of an athlete's total physical movement in collision-based team sport compared to GPS technology. There is limited evidence of the utility of accelerometers to detect positional and half differences in player movement during collision-based team sports when compared to GPS technology. The purpose of the present investigation was to determine the effectiveness of the respective technologies for detecting differences in measures of maximum mean movement between positions and halves during professional rugby union match-play using a 600-s rolling average epoch.

3.2 Methods

3.2.1 Participants

Movement data were collected via GPS and accelerometers for 30 male professional rugby union players (16 forwards, 14 backs) of an Australian National Rugby Championship team across an eight-match season. All players gave informed consent to participate and the study was approved by the Victoria University Human Research Ethics committee.

3.2.2 Equipment

Commercially available OptimEye™ S5 GPS and GLONASS-enabled receivers were used (firmware version 7.22, Catapult Sports, Melbourne, Australia), housing an inbuilt tri-axial piezoelectric accelerometer. Unfortunately the specific model of accelerometer used and many of its specifications were largely unavailable to the authors due to proprietary issues, so attempts were made to provide high-level descriptions to substitute where possible. The GPS receiver samples at 10 Hz with the integrated accelerometer using a micro-electromechanical system (MEMS) sampling at 100 Hz with an output range of ± 16 *g*. Prior to data collection, the receivers were turned on and left outside on the playing surface in an open area to attain a satellite connection before placing them on the rugby players. The small OptimEye™ receivers (96 × 52 × 14 mm, weighing 67 g) were placed within a custom-made pouch within the back of the player's playing uniform, situated between their scapulae. Each OptimEye™ S5 receiver contains its own microprocessor, gyroscopes (3D, 2000 deg $\cdot s^{-1}$, up to 1000 Hz), magnetometers (3D, 100 Hz, full scale of 1200 micro tesla), 2 GB internal flash memory, a high-speed USB interface to record, store and retrieve data, a lithium ion rechargeable battery with 6 hours life and is water resistant. Boyd et al. (Boyd et al., 2011) performed stability testing with two of the predecessor model accelerometers to that used in the present study (Catapult MinimaxX 2.0, Kionix: KXP94) in an environmental chamber to assess any drift from the baseline gravity measure. The MEMS receiver was designed to deliver a high signal to noise ratio with manufacturer specified operating temperature ranges from -40 to 85°C. Over three-hours the temperature was gradually increased from 15 to 35°C and was then reduced back to 15°C. The resultant change of 0.1 PlayerLoad™ arbitrary units (au, measure explained below) is negligible when considering PlayerLoad™ values in excess of 700 au are regularly observed in rugby union training and matches (Howe, unpublished observations). Environmental temperature and humidity across the eight match season (mean ± SD) was 18.8 ± 6.3°C and 42 ± 23% respectively. During acute whole-body dynamic exercise skin blood flow and temperature increases linearly with core temperature until approximately 38°C, beyond which any further elevation in core temperature provokes no further elevation in skin blood flow and temperature (González-Alonso et al., 1999). Therefore, the temperature of the accelerometer placed on the skin surface between the player's scapulae during a whole body dynamic task such as rugby union should not exceed the operating temperature ranges of the accelerometer used in the present study.

3.2.3 Measures of Maximum Mean Movement

Manufacturers of the technology used in the present study created a modified vector magnitude (PlayerLoad^{TM}), expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in three orthogonal planes, accumulated over time (1). The accumulated PlayerLoad^{TM} value is then divided by a scaling factor to reduce the value to make it easier to use. Creation of a vector magnitude such as PlayerLoad^{TM} that produces one value improves industry uptake of the technology and usability of the data.

$$\text{PlayerLoad}^{TM}\,(\text{accumulated})_{t=n} =$$

$$\sum_{t=0}^{t=n} \sqrt{(\text{fwd}_{t=i+1}-\text{fwd}_{t=i})^2+(\text{side}_{t=i+1}-\text{side}_{t=i})^2+\left(\text{up}_{t=i+1}-\text{up}_{t=i}\right)^2}$$

$$\text{for } t = 0, 0.01, 0.02, 0.03\ldots.n \tag{1}$$

Where: fwd = forwards acceleration, side = sideways acceleration, up = vertical acceleration, t = time

Metabolic power (Metabolic power) is a GPS derived measure of power that combines both velocity and acceleration based events. The metabolic power theoretical model proposed by di Prampero et al. (Di Prampero et al., 2005), considers the energy cost of accelerated running on a flat surface to be energetically equivalent to running on an equivalent uphill slope at a constant speed. If acceleration and velocity are known, the instantaneous metabolic power output ($W.kg^{-1}$) of each athlete may be calculated (for underlying mathematical principles see (Di Prampero et al., 2005; Osgnach et al., 2010). Mean speed ($m.min^{-1}$, GPS derived) expresses a player's absolute distance covered in a given time period.

3.2.4 Performance Evaluation Criterion

Given the applied field-based nature of the present study, a criterion measure (e.g., video analysis) to evaluate the respective GPS and accelerometer technologies against was not available. The sensitivity of the technologies to quantify differences that should exist between forwards and backs and between first and second halves was therefore compared. The *t*-statistic is the fundamental statistical measure of sensitivity (signal/noise or more specifically, change in the mean divided by the standard error). However the *t*-statistic does not provide a practical measure of the magnitude of effect, other than to convey whether the observed effect was different from zero or not. Expressing differences or changes in the mean in standardized units (dividing differences by an appropriate average of the between player standard deviations in the compared groups) provides a similar measure to *t*-statistics but is easier to interpret and practically use. Consequently, standardized effects were the primary statistical measure used to compare and evaluate performance of the respective technologies.

3.2.5 Statistical Analyses

General linear mixed modelling (PROC MIXED) was carried out using SAS to predict measures, with fixed effects for positional differences (backs, forwards), match half (1st, 2nd), and with random effects for between-player differences, within-player variabilities, and between-match differences. All data were log-transformed to reduce non-uniformity error. Effects were quantified using standardization and interpreted with magnitude-based inferences (Hopkins et al., 2009). Threshold values for standardized effects were: < 0.2 (trivial), > 0.2 (small), > 0.6 (moderate) and > 1.2

(large) (Hopkins et al., 2009). Effects were deemed *unclear* when the 90% compatibility limits crossed -0.2 and 0.2.

Raw GPS data were calculated using the Doppler-Shift method. Proprietary software (Catapult Sprint™ version 5.1.4) filtered the raw velocity, acceleration and subsequent metabolic power data using a median filter to reduce inherent signal noise (Varley et al., 2017a). Unfortunately, the processing algorithm for PlayerLoad™ was unavailable to authors due to proprietary issues, with unpublished calculations of raw PlayerLoad™ (calculated via raw individual axis data and use of the available PlayerLoad™ equation) providing values systematically divergent from manufacturer provided PlayerLoad™ values (Howe, unpublished observations). Player match movement files were cropped to include only match time using proprietary software. Further file inclusion criteria included: mean horizontal dilution of position (HDOP) of ≤ 1.5 and mean number of satellites ≥ 4. Individual player files were then exported to a comma-separated values (CSV) format from proprietary software into Microsoft Excel 2013 (version 15.0.4701.1001, Microsoft Corp, Redmond, WA, USA) and then imported into Statistical Analysis System software (version 9.4; SAS Institute, Cary, NC, USA) for further data processing. Within the SAS environment, statistical code was written to process the imported CSV files, with velocity spikes ≥ 11 $m.s^{-1}$ and maximum accelerations ≥ 6 $m.s^{-2}$ (unrealistic values) removed and only player files ≥ 600-s field time included. The mean ± SD number of satellites and HDOP during matches was 14.3 ± 1.7 and 0.8 ± 0.2, respectively, indicative of good GPS signal quality as per manufacturer's recommendations. A total of 256 match-half files remained for further analysis.

3.3 Results

All *t*-statistics directly paralleled the standardized effects for both positional and half differences, thus only standardized half (Figure 3.1) and positional (Figure 3.2) effects are presented.

Figure 3.1 illustrates the maximum mean half standardised effects (1st – 2nd half) over a 600-s rolling epoch duration by positional group (forwards and backs). For both forwards and backs, accelerometer-derived PlayerLoad^{TM} displayed larger standardised match-half effects when compared to GPS derived measures of metabolic power and mean speed. For instance, GPS metrics measured a small standardised increase (ES > 0.2) in mean speed and metabolic power in the first half compared to the second halves for backs, whilst PlayerLoad^{TM} measured a moderate standardised increase (ES > 0.6) in the first match-half compared to the second.

Figure 3.2 displays the maximum mean positional standardized effects (backs - forwards) over a 600-s rolling epoch by half. Positional differences between backs and forwards as measured by accelerometer-derived PlayerLoad^{TM} displayed clear moderate to large standardized differences, as opposed to unclear or less likely positional differences quantified by both GPS measures.

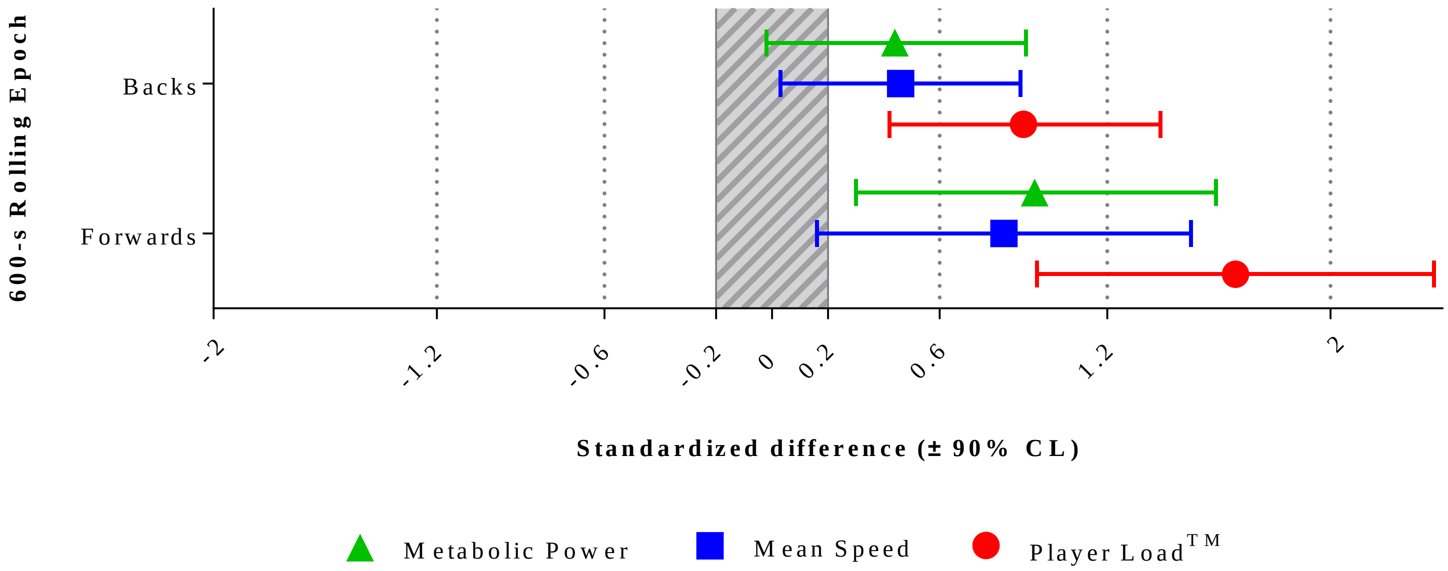

Figure 3.1 Maximum mean half standardized effects (1st – 2nd half) over a 600-s rolling epoch by position.

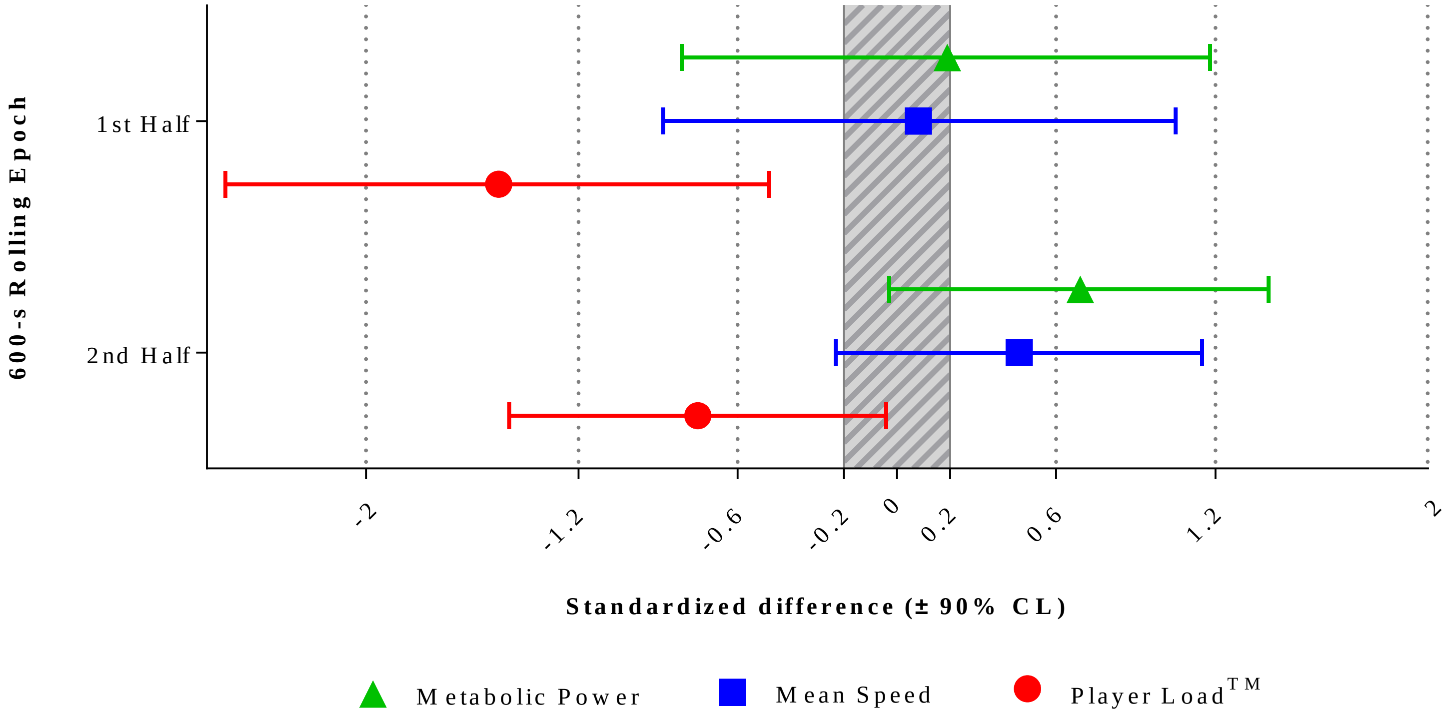

Figure 3.2 Maximum mean positional standardized effects (backs - forwards) over a 600-s rolling epoch by half.

3.4 Discussion

Accelerometers outperformed GPS in quantifying positional and half differences in player maximum mean movement during professional rugby union match-play. Accelerometer derived PlayerLoad^{TM} was more sensitive for quantifying declines in maximum mean movement in the second half compared to the first half for both playing positions (up to a 17.6% decline), indicated by larger positive standardized effects than either GPS measure (Figure 3.1). Positional differences between backs and forwards were also more adequately quantified by accelerometer technology, with *clear* moderate to large standardized differences observed, as opposed to *unclear* or less *likely* positional differences quantified by GPS measures (Figure 3.2). Relative to the backs, the forwards produced greater PlayerLoad^{TM} per unit of distance covered or metabolic power generated. This finding is in line with forwards spending more time in physical contact with the opposition and completing more total work throughout a match than backs (Duthie et al., 2003). If sporting practitioners were to solely use GPS technology to quantify and monitor activity profile differences between players and positions, many movements performed frequently by forwards that incur little horizontal displacement (e.g., collisions) would be severely underestimated. Misrepresentive quantification of physical movement during matches and training may lead to training workload errors, maladaptation or heighten the likelihood of illness or injury. However, GPS still provide valuable activity profile contextual information practitioners can use to help quantify, monitor and prescribe subsequent training from.

The different technologies provided different results fundamentally because accelerometers primarily measure vertical displacement, whereas GPS technology primarily measures horizontal displacement. It is recommended that practitioners select technologies and measures depending on the primary sporting movements of interest (i.e., use the right tool for the job). As collision-based team sports involve many movements comprising both vertical and horizontal displacement, both technologies should be used.

3.5 Conclusions and Practical Applications

Accelerometers outperformed GPS in quantifying important differences in athlete movement between positions and halves during rugby union match-play. The use of GPS technology alone underestimates movement of collision-based team sport athletes. Accelerometers provide meaningful additional information to GPS technology that may aid practitioners in physically preparing and monitoring collision-based team sport athletes.

CHAPTER 4: STUDY 2 - SENSITIVITY, RELIABILITY AND CONVERGENT VALIDITY OF GPS AND ACCELEROMETERS FOR QUANTIFYING PEAK PERIODS OF RUGBY COMPETITION

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4.1 Introduction

Using wearable global positioning systems (GPS) and inertial sensors to quantify athletic movement is an application of the technology long preceded by navigation and military applications (Lachow, 1995). Quantification of athletic movement via wearable technology is important for sporting practitioners as it provides objective data to inform the decision-making process around training load management (Gallo et al., 2015), training prescription (Delaney et al., 2015), player readiness to play (Barrett et al., 2016), injury risk (Gabbett et al., 2011a), and player interchange decisions (Aughey et al., 2010; Delaney et al., 2016c). The prolific adoption of GPS with integrated inertial sensor technology in elite team sports is testament to its perceived worth and impact on player and team preparation and performance.

Position, velocity and distance can be derived via GPS (Larsson, 2003). Subsequently, change in velocity (acceleration and deceleration) may be calculated (Varley et al., 2012b) and potentially used in combination with velocity-based events to estimate the energy cost of exercise (metabolic power) (Di Prampero et al., 2005). Whilst GPS athlete tracking data can be of great value to practitioners, it has reduced validity and reliability for quantifying rapid changes of direction (Rawstorn et al., 2014) and velocity (Akenhead et al., 2014; Jennings et al., 2010), estimating metabolic power (Buchheit et al., 2015) and for assessing short duration, high-velocity tasks that frequently occur in team sports (Coutts et al., 2010a; Jennings et al., 2010). Movements that incur little horizontal displacement (e.g., collisions, tackles and many sport-specific movements) are also likely to be underestimated by GPS (Boyd et al., 2013). Further, positional and match-half differences in athlete maximal movement were underestimated by GPS technology when compared to accelerometers during professional rugby union match-play (Chapter 3). In light of these findings, authors recommended that researchers and practitioners use accelerometers alongside GPS technology to adequately quantify important positional differences and match-half changes in athlete movement during collision-based team sports.

Manufacturers of accelerometer technology used by sporting practitioners and scientists have created modified vector magnitude proprietary algorithms, with frequently published measures being PlayerLoad™ (Catapult Sports) (Boyd et al., 2013) and BodyLoad™ (GPSports) (Weaving et al., 2014). Vector magnitudes sum the squared instantaneous rate of change in acceleration in three orthogonal axes accumulated over time, providing an estimate of totality of movement often referred to as external load. Accelerometers have been used to quantify athlete external load (Boyd et al., 2013) and energy expenditure (Walker et al., 2015) during training and competition, with PlayerLoad™ moderating the recovery response of footballers (Rowell et al., 2016). Accelerometers are reliable in laboratory (Kelly et al., 2015) and field settings (Boyd et al., 2011) and can accurately detect individual contact events (Hulin et al., 2017), sport-specific movements (McNamara et al., 2015), and alterations in movement strategies, efficiency or kinematic changes (Barrett et al., 2016; Cormack et al., 2013). Unlike GPS, accelerometers can also operate within indoor environments, providing greater utility (Aughey, 2011). Accelerometers provide valuable additive external load information to GPS that may aid practitioners in more accurately quantifying player totality of movement in collision-based team sports (Chapter 3). Quantifying external load during collision-based team sports may help practitioners to prescribe and monitor training in a more objective manner, carefully balancing the need for physiological and biomechanical load to induce positive adaptations whilst mitigating overuse to reduce injury likelihood, or put more simply, balance fitness and fatigue (Banister, 1991).

Team sports that contain a substantial collision-based component (e.g., rugby union, rugby league, National Football League and Australian Rules Football) are characterised by low-intensity activity interspersed with frequent bouts of high-intensity activity (Aughey, 2010; Deutsch et al., 2007). Despite the majority of team sport competition being spent at submaximal intensity, high-intensity activities are often aligned with key events that determine match outcome (Faude et al., 2012; Gabbett et al., 2016), signifying the importance of physically conditioning athletes for these intense periods of match-play. The most intense or peak periods of football competition do not often fall completely within a pre-defined period of time and therefore these methods underestimate the most intense periods of match-play and overestimate subsequent periods of activity (Cunningham et al., 2018; Ferraday et al., 2020; Varley et al., 2012a). During elite soccer competition the peak periods of high-velocity running distance were identified using either pre-defined (distance covered in 5-minutes at every 5-minute time point) or rolling time periods (distance covered in 5 minutes from every time point). Rolling or moving average methods involve analysing raw instantaneous data from the device used. For example, GPS receiver data are commonly sampled at 10 Hz (i.e. ten times per second) and accelerometer data typically at 100 Hz (i.e. one hundred times per second). To identify the peak periods of competition using a moving average approach, one must select a duration of interest (e.g. 5 minutes), with that window of time then moved across every second of the competition, collecting a moving average from every single time point. For example, using a one-minute window that equates to 600 samples (60 s with ten samples per second using 10 Hz GPS), the moving average would be applied to a player's match data file as follows: 0-600, 1-601 s, 2-602 s, 3-603 seconds etc., to identify the one-minute peak measure/s of interest (Whitehead et al., 2018b). During professional soccer competition, peak high-velocity running distance was underestimated by up to 25% using pre-defined time period analysis, with the subsequent period distances overestimated by up to 31% when compared to rolling time period analysis. When the distance decline in high-velocity running between the peak and following period were examined, there was up to a 52% greater reduction in running performance using rolling vs. pre-defined periods (Varley et al., 2012a). Likewise during international rugby competition, both high-speed running (>5 $m.s^{-1}$) and relative distance ($m.min^{-1}$) were consistently underestimated by pre-defined compared to rolling period analyses of 60 – 300 seconds (Cunningham et al., 2018). Pre-defined epoch analyses on average underestimated relative distances covered by ~ 11% and high-speed running by up to ~ 20% compared to rolling epoch analyses, with the greatest underestimations occurring using the 60 second epoch (95% compatibility interval, high-speed running: -6.05 to -4.70 $m.min^{-1}$, relative distance: -18.45 to -16.43 $m.min^{-1}$) (Cunningham et al., 2018). Similarly in English Championship soccer matches, pre-defined epoch analyses of 60

– 600 seconds underestimated peak movement intensities of competition when compared to rolling epoch analyses for both total distance (∼7–10%) and high-speed (∼12–25%) distance, irrespective of playing position (Ferraday et al., 2020). Therefore, it is recommended that researchers and practitioners use rolling/moving time period analyses when trying to accurately identify and quantify the peak periods of football competition (Varley et al., 2012a).

Duration- and position-specific player movement differences have been observed during the most intense periods of match-play across various football codes including: rugby league (Delaney et al., 2015), rugby union (Delaney et al., 2016d), Australian Rules Football (Delaney et al., 2017a) and soccer (Delaney et al., 2017b). These investigations provided valuable insights into the highly intermittent nature of team sport movement and highlighted that rolling time-motion analyses may assist practitioners in the design and prescription of training that is more representative and specific to competition. However, the sensitivity, reliability and convergent validity of GPS- and accelerometer-derived measures for quantifying player movement during the most intense periods of match-play in team sports is not known, limiting a practitioner's ability to interpret and use such data to inform practice. Our aim was therefore to determine the sensitivity, reliability and convergent validity of measures derived from GPS and accelerometer technology to quantify the most intense periods of rugby union match-play.

4.2 Methods

4.2.1 Participants

Movement data were collected via integrated GPS and accelerometer receivers for 60 professional rugby union players (30 elite and 30 sub-elite) across two team's respective seasons. The 30 elite players (18 forwards and 12 backs) played in the 2015 Super 15

Rugby competition, an international rugby union competition played between 5 Australian, 5 New Zealand and 5 South African teams. The Super 15 competitive season comprised of 18 rounds with 2 bye rounds per team, making 16 total matches (8 home, 8 away). The 30 sub-elite players (16 forwards and 14 backs) played in the 2014 National Rugby Championship, an Australian competition played between 9 teams from 5 states and territories, with the season comprising of 8 matches (4 home, 4 away) prior to a finals series for the top 4 finishing teams. The National Rugby Championship is the highest standard of rugby union played in Australia below Super 15 and international representative rugby. The data set for sub-elite includes 7 regular season matches and the semi-final (8 matches total), as 1 match did not meet our inclusion criteria (see methods for inclusion criteria, data filtering and processing section). Players were grouped by playing position into forwards and backs rather than more specific playing positions (e.g., prop, centre, scrum-half) to increase precision of estimates and to first assess if the respective technologies were sensitive enough to quantify broader positional classifications prior to comparing specific positional groupings. Elite and sub-elite participant numbers and physical characteristics can be seen in Table 4.1. All players gave informed consent to participate and the study was approved by the Victoria

University Human Research Ethics Committee.

Table 4.1 Participant numbers and physical characteristics of the rugby union players

	Elite (Super 15)	Sub-elite (NRC)
Number of participants	30	30
Number of forwards	18	16
Number of backs	12	14
Mean age (y)	25 ± 4	24 ± 4
Mean height (cm)	187 ± 7	185 ± 7
Mean body mass (kg)	106 ± 12	106 ± 13
Forwards age (y)	25 ± 4	24 ± 3
Forwards height (cm)	187 ± 8	187 ± 8
Forwards body mass (kg)	113 ± 8	115 ± 10
Backs age (y)	25 ± 4	24 ± 4
Backs height (cm)	185 ± 5	183 ± 5
Backs body mass (kg)	95 ± 6	96 ± 9

4.2.2 Equipment and Data Collection

Match movement data were collected via commercially available OptimEye^{TM} S5 GPS and GLONASS-enabled receivers with an embedded tri-axial piezoelectric accelerometer (firmware version 7.22, Catapult Sports, Melbourne, Australia). Prior to data collection during match-play, the receivers were turned on and left outside on the playing surface in an open area to attain a satellite connection before placing them on the rugby players. The receivers (96 mm × 52 mm × 14 mm, weighing 67 g) were placed within a custom-made tightly-fitting pouch within the back of the player's playing uniform, situated between their scapulae. To minimize inter-receiver variability, each player was assigned the same receiver for the entirety of the respective seasons (Buchheit et al., 2014).

Manufacturers of the technology used in the present study did not reveal to authors the specific model of accelerometer. However, we have attempted to provide high level specification descriptions of the technology used where possible. Sampling frequencies for the GPS and tri-axial accelerometer were 10 Hz and 100 Hz respectively, with the accelerometer having an output range of ±16 *g*. Each receiver has its own microprocessor, gyroscopes (3D, 8000 $deg \cdot s^{-1}$, up to 1000 Hz), magnetometers (3D, 100 Hz, full scale of 1200 micro tesla), 2 GB internal flash memory, 250 m wireless frequency transmission, a high-speed USB interface to record, store and retrieve data, a lithium ion rechargeable battery with 6-hours life and is water resistant. Accelerometer signal drift errors from the baseline gravity measure are negligible with temperature changes from 15 to 35°C, using the predessor model accelerometer (Catapult MinimaxX 2.0, Kionix: KXP94) to that used in the present study (Boyd et al., 2011). Positioning the accelerometer between player's scapulae near the surface of the skin during a whole-body dynamic task such as rugby union should not exceed the manufacturer specified operating temperature ranges of -40 to 85°C.

4.2.3 Measures of Maximum Mean Movement

The three measures of maximum mean or peak movement investigated were: Playerload^{TM} (au, accelerometer-derived), mean speed ($m.min^{-1}$, GPS-derived) and metabolic power ($W.kg^{-1}$, GPS-derived) as they provide estimates of global external load and are frequently reported in research and used in practice. Acceleration, total distance, high-speed running distance and estimated metabolic power were ranked as the most important variables in the eyes of elite football practitioners (Akenhead et al., 2016), lending further support for the chosen measures.

PlayerLoad™ is a Catapult Sports proprietary vector magnitude, mathematically expressed as the square root of the sum of the squared changes in acceleration in three orthogonal planes over the sampling interval (set at 100 Hz). PlayerLoad™ = $\sqrt{(\Delta Forward^2 + \Delta Side^2 + \Delta Up^2)}$, where Forward, Side and Up refer to directions of acceleration, and Δ refers to the change over the sampling interval (10 ms) (Boyd et al., 2011). The receivers of acceleration are $m.s^{-2}$, but the Catapult software applies an arbitrary unknown scaling factor when this measure is accumulated and may have applied such a factor to this "instantaneous" measure. We have therefore shown its units as arbitrary (au).

Metabolic power is a GPS-derived measure of power that considers the energetic cost of accelerated running on flat terrain to be energetically analogous to running on an equivalent uphill slope at a constant speed (Di Prampero et al., 2005). Instantaneous metabolic power output ($W.kg^{-1}$) of an individual may subsequently be calculated if acceleration and velocity is known (Di Prampero et al., 2005; Osgnach et al., 2010). Whilst the measure was lauded and widely applied when first published, extensive validity and reliability testing had not yet been carried out. The application of metabolic power in team sports has been questioned in recent years (Buchheit et al., 2015; Highton et al., 2016), yet its perceived importance and application is still prevalent (Akenhead et al., 2016). We were therefore interested to investigate whether metabolic power has merit for quantifying external load during the most intense periods of a collision-based team sport like rugby union.

Mean speed or relative distance ($m.min^{-1}$) is a GPS-derived measure that expresses the absolute distance an athlete covers relative to the time they spent on the field. For instance, if an athlete covers 8000 m during an 80 minute rugby union match; their relative distance would be 100 $m.min^{-1}$. Quantification of mean speed or relative distance may assist subsequent training prescription and monitoring of intensity and enables reasonable comparison between full-match and substitution players and between different sporting codes (Aughey, 2011).

4.2.4 Data Filtering and Processing

The Doppler-shift method (change in frequency of the satellite signal) was used to calculate the raw GPS data (Townshend et al., 2008). The raw velocity and subsequent acceleration and metabolic power data were filtered by proprietary software (Catapult Sprint™ version 5.1.4) using a median filter to reduce inherent signal noise (Varley et al., 2017b). Acceleration derived via GPS used for the calculation of metabolic power was derived over a 0.2 second time interval (smoothing filter width as defined in the software). The intelligent motion filter option provided within Catapult Sprint™ software was not activated. The processing algorithm for PlayerLoad™ was unfortunately not available to authors for proprietary reasons.

Player match movement files were cropped to include only match time using Catapult Sprint™. Individual player files were then exported from Catapult Sprint™ via comma-separated values files into Microsoft Excel 2013 (version 15, Microsoft Corp, Redmond, WA, USA) and then imported into the Statistical Analysis System (SAS, version 9.4; SAS Institute, Cary, NC) for further data processing. A program was written within SAS to identify the maximum mean value of each measure (PlayerLoad™, mean speed and metabolic power) using a rolling moving average of a given duration (5, 10, 20, 30, 60, 120, 300 and 600 seconds). Stringent data inclusion criteria were applied to individual player files before performing further analyses. Data inclusion criteria for individual player files included mean horizontal dilution of position (HDOP) of ≤ 1.5, mean number of satellites ≥ 4, and ≥ 600 seconds spent on field. Unrealistic velocity spikes ≥ 11 m.s^{-1} and maximum accelerations ≥ 6 m.s^{-2} were also removed during this process. The mean ± standard deviation (SD) number of satellites for the elite and sub-elite cohort's data sets were 13.5 ± 1.1 and 14.3 ± 1.7 respectively, whilst HDOP was 0.9 ± 0.3 and 0.8 ± 0.2 respectively. These values are indicative of good GPS signal quality as per manufacturer's recommendations. A total of 421 elite and 256 sub-elite player match-half files remained for further analysis.

4.2.5 Statistical Analyses

Each of the three measures of maximum mean movement was analysed with the general linear mixed modelling procedure (Proc Mixed) in SAS. The measures were log-transformed prior to analysis to reduce non-uniformity of error (Hopkins et al., 2009) and to express effects and errors in percent units after back-transformation. The fixed effects in the model were player position (backs, forwards) interacted with match-half (1^{st}, 2^{nd}) to provide estimates of least-square means and differences between the means of these variables; these effects were also interacted with time on the field (numeric linear) to produce maximum mean values that adjust to the average time a player is on the field across the positions and halves. The random effects in the model were player identity (to estimate differences between player means), match identity (to estimate differences between match means), the interaction of player and match identities (to estimate changes within players between matches); different variances were estimated for the random effects for the two positions (forwards, backs). The residual in the model estimated within-athlete variability (typical error or "noise") between match halves; different residual variances were estimated for the four position*half groups and to simplify presentation were averaged. The random effects were combined into intraclass correlation coefficients (ICCs) representing reliability of each measure. Compatibility limits for the correlations were generated with a bootstrap method, in which the independent standard errors of the variances provided by the mixed model were combined with random normal deviates to generate bootstrap samples.

The magnitudes of effects (differences or changes in means; standard deviations derived from random effects) were evaluated by standardisation, which was performed by dividing each effect by the between-player standard deviation in a typical match. This standard deviation was derived for ease of calculation from four separate analysis (for each position and half) by adding the variances for the random effects for player identity and the residual, converting the resulting variances to standard deviations and deriving the harmonic mean, which provided an appropriate mean standard deviation for all pairwise comparisons of positions and halves (Hopkins, 2007b). The smallest worthwhile difference or change in means (the "signal", for comparison with "noise") is 0.2 standard deviations; thresholds for moderate, large and very large differences are 0.6, 1.2 and 2.0, respectively (Hopkins et al., 2009). Thresholds for evaluating standard deviations (derived by taking square roots of random-effect variances) were half these values (Smith et al., 2011). Typical error was evaluated via the following thresholds: < 0.5 neligable error, 0.5-1.5 small, 1.5-3 moderate, 3-6 large, 6-10 very large > 10 extremely large.

Uncertainty in effects was expressed as 90% compatibility limits and as probabilities that the true effect was substantially positive and negative (derived from standard errors, assuming a normal sampling distribution). These probabilities were used to make a qualitative probabilistic non-clinical magnitude-based decisions about the true effect (Hopkins et al., 2009): if the probabilities of the effect being substantially positive and negative were both > 5%, the effect was reported as unclear; the effect was otherwise clear and reported as the magnitude of the observed value, with the qualitative probability that the true effect was a substantial increase, a substantial decrease, or a trivial difference (whichever outcome had the largest probability). The scale for interpreting the probabilities was as follows: 25–75%, possible; 75–95%, likely; 95-99.5%, very likely; > 99.5%, most likely.

For a sample size of approximately 50, standardised residuals (*t*-statistics) of > 3.5 can be considered outliers (Hopkins et al., 2009). Considering the cohort size (60 participants, 30 in each group) and the number of subsequent player files in each cohort (421 and 256 files respectively), a standardised residual outlier threshold of > 3.5 was applied, with those above the threshold removed.

4.2.5.1 Evaluating Sensitivity

Sensitivity of measures was quantified via evaluation of the smallest worthwhile difference or change in means ("signal") and typical error of measurement ("noise"). The smallest worthwhile difference (SWD) is 0.2 between player standard deviations of a given position in a typical game; thresholds for moderate, large and very large differences are 0.6, 1.2 and 2.0, respectively (Hopkins et al., 2009). To estimate the typical error or noise of each measure, the difference between observed and predicted values (the residual) was added as a random effect in the general linear mixed model as stated previously.

4.2.5.2 Evaluating Reliability

Variabilities within and differences between players represented reliability of each measure. The random effects of player identity, interaction of player and match identities and the residuals were combined into intraclass correlation coefficients, representing reliability of each measure between-halves within a match and within halves, between matches. Magnitudes of ICCs were evaluated using the following thresholds: > 0.99, extremely high; ≤ 0.99 to ≥ 0.90, very high; < 0.90 to ≥ 0.75, high; < 0.75 to ≥ 0.50, moderate; < 0.50 to ≥ 0.20, low; < 0.20, very low (Hopkins, 2015).

4.2.5.3 Evaluating Convergent Validity

Convergent validity is a type of construct validity (i.e. tool measures what it is supposed to measure) that reflects the extent to which two measures capture a common construct (Carlson et al., 2012). Convergent validity of the three measures (mean speed, PlayerLoad^{TM} and metabolic power) was assessed by comparing mean differences between playing positions and match halves with findings from previous rugby union time-motion analyses that use other tools (e.g. other GPS and accelerometer models, local positioning systems, optical systems, notational analysis etc.) and measures (several high-intensity metrics) to quantify a common construct (i.e. player movement). More specifically, many rugby union time-motion analyses have observed differences in high-intensity movement between playing positions and match-halves (Cunningham et al., 2018; Delaney et al., 2016d; Deutsch et al., 2007; Duthie et al., 2003; Jones et al., 2015; Roe et al., 2016). If the peak intensity of competition differences observed in the present study were consistent with expected positional and match-half activity profiles from previous studies, then the measures were deemed to "converge" or relate to previous findings and display convergent validity. For example, if the weight of rugby time-motion analysis literature revealed that backs produce greater maximal speeds and accelerations than forwards during competition, and the mean speed and metabolic power measures used in the present study quantified similar positional differences, the measures display some level of convergent and construct validity.

4.3 Results

Duration-specific grand means and standard deviations (SD) of each measure of maximum mean movement are shown in Tables 4.2, 4.3 & 4.4 to provide context for the positional differences and match-half changes. The random effect for match identity showed that the maximum mean (peak) intensity of matches varied typically by 3-6%, 2-6% and 0-6% for mean speed, metabolic power and PlayerLoad™ respectively.

4.3.1 Sensitivity of Measures

Global positioning system and accelerometer measures had poor sensitivity for quantifying maximum mean movement across all epochs and both levels of competition, with noise 4× to 5× the signal (Tables 4.2, 4.3 & 4.4). Elite 5-600 second maximum mean typical error ranges across positional groups and halves were 8-14%, 8-17% and 7-15% for mean speed, metabolic power and PlayerLoad™ respectively. Similarly, for the sub-elite cohort the typical error ranges were 6-12%, 6-18% and 6-16% respectively. When comparing the within (typical error) and between player average standard devations, the typical error was ~ 0.8-1.0 the between subject SD, indicative of large (>0.6) to very large (>1) error, which was 8 to 10 fold greater than the smallest important error (0.1) (Smith et al., 2011).

4.3.2 Within-Match, Between-Half Reliability

Maximum mean movement measured via GPS- and accelerometer-derived measures displayed very low to moderate within-match, between-half reliability (ICC range; 0.0 to 0.7) during both sub-elite and elite rugby union match-play. Maximum mean PlayerLoad™ displayed higher within-match, between-half reliability in the elite cohort than either mean speed or metabolic power for epoch durations ≥ 60 seconds, although this test-retest reliability was still low (ICC ~ 0.4). For the sub-elite backs, mean speed and metabolic power generally had slightly higher ICCs (~ 0.4) than PlayerLoad™ (~ 0.2) for epochs ≥ 30 seconds.

Table 4.2 Maximum mean mean speed ($m.min^{-1}$) descriptive, effect and inferential statistics for rolling epoch durations of 5 to 600-s within elite and sub-elite rugby union competition.

Epoch duration (s)	Grand mean ($m.min^{-1}$)	Between-subject SD (%)	Typical error (%)	SWD (%)	Positional differences (backs – forwards) Mean; ±90%CI (%)	Inference[a]	Match-half change (second – first half) Mean; ±90%CI (%)	Inference[a]
Super 15 Rugby (elite)								
5	380	12.3	10.1	2.5	19.8; ± 6.9	Large ↑****	-3.7; ± 1.7	Small ↓**
10	309	13.6	12.3	2.7	18.3; ± 6.7	Large ↑****	-5.4; ± 2.1	Small ↓***
20	235	12.7	12.0	2.5	15.6; ± 5.5	Large ↑****	-4.8; ± 2.0	Small ↓***
30	201	11.0	11.1	2.2	14.5; ± 5.0	Large ↑****	-5.1; ± 1.9	Small ↓***
60	155	9.8	10.1	2.0	11.7; ± 4.6	Large ↑****	-3.2; ± 1.7	Small ↓**
120	123	9.5	9.8	1.9	8.2; ± 4.9	Moderate ↑***	-2.6; ± 1.7	Small ↓**
300	91	10.6	11.1	2.1	7.8; ± 5.4	Moderate ↑***	-6.6; ± 1.8	Moderate ↓****
600	76	9.7	9.9	1.9	9.1; ± 6.3	Moderate ↑***	-5.7; ± 1.7	Moderate ↓****
National Rugby Championship (sub-elite)								
5	387	13.6	11.5	2.7	22.3; ± 9.6	Large ↑****	-3.8; ± 5.8	Small ↓*
10	320	14.1	12.1	2.8	22.9; ± 10.5	Large ↑****	-1.6; ± 6.3	Trivial
20	236	12.3	11.3	2.5	22.3; ± 9.4	Large ↑****	2.1; ± 5.9	Small ↑
30	201	11.8	10.0	2.4	13.7; ± 8.8	Moderate ↑***	0.6; ± 5.4	Trivial
60	158	10.0	8.9	2.0	10.2; ± 7.3	Moderate ↑***	-3.6; ± 3.7	Small ↓**
120	128	10.3	9.4	2.1	8.9; ± 7.6	Moderate ↑**	-6.2; ± 4.1	Moderate ↓***
300	98	10.0	9.5	2.0	4.3; ± 8.4	Small ↑	-2.3; ± 4.8	Small ↓
600	82	10.1	8.0	2.0	2.7; ± 7.6	Small ↑	-6.2; ± 3.7	Moderate ↓***

Grand means represent the mean of pooled positional (backs, forwards) and match-half (first, second) data.
SWD, smallest worthwhile difference (0.2 of between-subject SD); 90%CI, 90% compatibility interval.
[a]Inferences specify the magnitude, direction and likelihood of the true value of clear effects. Magnitudes were defined by standardisation (see text). Likelihood for clear trivial effects: [0]possible, [00]likely, [000]very likely. Likelihood for clear substantial effects: *possible, **likely, ***very likely, ****most likely.

Table 4.3 Maximum mean metabolic power (W.kg^{-1}) descriptive, effect and inferential statistics for rolling epoch durations of 5 to 600-s within elite and sub-elite rugby union competition.

Epoch duration (s)	Grand mean (W.kg^{-1})	Between-subject SD (%)	Typical error (%)	SWD (%)	Positional differences (backs – forwards) Mean; ±90%CI (%)	Positional differences (backs – forwards) Inference[a]	Match-half change (second – first half) Mean; ±90%CI (%)	Match-half change (second – first half) Inference[a]
Super 15 Rugby (elite)								
5	54.9	16.8	13.1	3.4	30.0; ±10.1	Large ↑****	-1.5; ±2.3	Trivial [00]
10	41.2	16.7	13.7	3.3	29.3: ±9.4	Large ↑****	-4.3; ±2.3	Small ↓**
20	29.9	15.1	13.1	3.0	24.6; ±7.3	Large ↑****	-4.3; ±2.2	Small ↓**
30	25.0	12.7	11.9	2.5	23.5; ±6.1	Large ↑****	-4.6; ±2.0	Small ↓***
60	18.7	12.1	11.0	2.4	17.3; ±6.4	Large ↑****	-3.6; ±1.9	Small ↓**
120	14.3	11.8	10.6	2.4	11.8; 6.6	Moderate ↑***	-3.3; ±1.8	Small ↓**
300	10.3	12.5	12.0	2.5	11.6; ±6.5	Moderate ↑***	-7.0; ±2.0	Moderate ↓****
600	8.4	11.7	11.6	2.3	11.9; ±7.0	Moderate ↑***	-7.0; ±2.0	Moderate ↓****
National Rugby Championship (sub-elite)								
5	54.2	16.6	13.6	3.3	34.8; ±13.6	Large ↑****	-6.8; ±6.3	Small ↓**
10	41.4	17.2	14.2	3.4	35.9: ±14.3	Large ↑****	-4.9; ±6.8	Small ↓*
20	29.0	14.3	12.2	2.9	35.6; ±12.2	V. Large ↑****	1.1; ±6.6	Trivial
30	23.7	13.0	9.6	2.6	28.5: ±11.1	V. Large ↑****	3.9; ±5.6	Small ↑*
60	18.3	11.5	9.5	2.3	19.4; ±9.0	Large ↑****	-4.3; ±4.3	Small ↓**
120	14.4	11.3	10.4	2.3	17.0; ±8.9	Large ↑****	-7.7; ±4.7	Moderate ↓***
300	10.9	10.6	9.9	2.1	8.8; ±9.4	Moderate ↑**	-4.6; ±4.9	Small ↓**
600	9.0	11.2	8.7	2.2	4.9; ±8.9	Small ↑	-7.3; ±4.0	Moderate ↓***

Grand means represent the mean of pooled positional (backs, forwards) and match-half (first, second) data.
SWD, smallest worthwhile difference (0.2 of between-subject SD); 90%CI, 90% compatibility interval.
[a]Inferences specify the magnitude, direction and likelihood of the true value of clear effects. Magnitudes were defined by standardisation (see text). Likelihood for clear trivial effects: [0]possible, [00]likely, [000]very likely. Likelihood for clear substantial effects: *possible, **likely, ***very likely, ****most likely.

Table 4.4 Maximum mean PlayerLoad^{TM} descriptive, effect and inferential statistics for rolling epoch durations of 5 to 600-s within elite and sub-elite rugby union competition.

Epoch duration (s)	Grand mean (au)	Between-subject SD (%)	Typical error (%)	SWD (%)	Positional differences (backs – forwards) Mean; ±90%CI (%)	Positional differences (backs – forwards) Inference[a]	Match-half change (second – first half) Mean; ±90%CI (%)	Match-half change (second – first half) Inference[a]
Super 15 Rugby (elite)								
5	3.8	15.9	13.5	3.2	7.4; ±6.5	Small ↑**	-0.8; ±2.4	Trivial ^{00}
10	2.8	15.3	12.1	3.1	7.0; ±6.8	Small ↑**	-1.2; ±2.2	Trivial ^{00}
20	2.0	13.6	11.0	2.7	1.9: ±5.8	Small ↑	-0.2; ±0.2	Trivial ^{000}
30	1.8	12.2	9.8	2.4	-0.9; ±5.2	Trivial	-0.2; ±1.8	Trivial ^{000}
60	1.4	12.7	8.7	2.5	-5.3; ±5.9	Small ↓**	-0.2; ±1.7	Trivial ^{000}
120	1.1	13.6	9.8	2.7	-11.3; ±6.3	Moderate ↓***	0.1; ±1.8	Trivial ^{000}
300	0.7	13.9	10.2	2.8	-11.4; ±7.2	Moderate ↓***	-2.5; ±1.8	Small ↓*
600	0.6	14.1	9.8	2.8	-11.9; ±7.7	Moderate ↓***	-1.8; ±1.7	Trivial ^{00}
National Rugby Championship (sub-elite)								
5	3.5	15.5	14.0	3.1	15.5; ±10.1	Moderate ↑***	2.5; ±6.8	Small ↑
10	2.7	15.6	14.4	3.1	12.6; ±9.7	Moderate ↑***	-2.7; ±6.6	Small ↓
20	2.0	12.9	12.1	2.6	10.1; ±8.2	Moderate ↑**	-0.9; ±6.2	Trivial
30	1.6	10.6	9.7	2.1	8.5; ±6.9	Moderate ↑**	2.8; ±5.1	Small ↑
60	1.3	9.3	8.5	1.9	0.6; ±5.0	Trivial	-8.3; ±3.5	Moderate ↓****
120	1.0	10.0	10.5	2.0	-3.7; ±6.3	Small ↓	-12.4; ±4.3	Large ↓****
300	0.7	9.5	9.7	1.9	-6.9; ±6.9	Moderate ↓**	-8.8; ±4.4	Moderate ↓***
600	0.6	10.0	8.1	2.0	-10.4; ±6.8	Moderate ↓***	-11.8; ±3.7	Large ↓****

Grand means represent the mean of pooled positional (backs, forwards) and match-half (first, second) data.
SWD, smallest worthwhile difference (0.2 of between-subject SD); 90%CI, 90% compatibility interval.
[a]Inferences specify the magnitude, direction and likelihood of the true value of clear effects. Magnitudes were defined by standardisation (see text). Likelihood for clear trivial effects: ^{0}possible, ^{00}likely, ^{000}very likely. Likelihood for clear substantial effects: *possible, **likely, ***very likely, ****most likely.

4.3.3 Between-Match, Within-Half Reliability

Reliability of maximum mean movement within a specific match-half from match-to-match was generally very low to low for all measures (ICC < 0.5), with movement reliability typically increasing with rolling epoch duration. PlayerLoad™ generally had lower reliability when compared to either GPS-derived measure for both sub-elite forwards and backs for epoch durations ≥ 60 seconds in the 2nd match-half. However, during elite match-play maximum mean movement quantified by accelerometer-derived PlayerLoad™ generally had higher between-match, within-half reliability when compared to mean speed and metabolic power. As the epoch duration increased in the elite cohort, so too did the reliability of maximum mean PlayerLoad™, with moderate to high ICCs for both positions and match halves for the 300 and 600-s epochs respectively (ICC range 0.5 to 0.8).

4.3.4 Playing Position Differences in Maximum Mean Movement

Relative to the backs, forwards had greater accelerometer-derived PlayerLoad™ per unit of distance covered or metabolic power across all rolling epochs (5 to 600-s), during both elite and sub-elite rugby union match-play (Figures 4.1 & 4.2). Elite backs produced clearly greater maximum mean speed and metabolic power compared to elite forwards for all rolling epoch durations (Table 4.2). A similar result was observed for the sub-elite cohort, with backs producing moderate to large higher mean speeds and large to very large higher metabolic power compared to the forwards for the shorter duration epochs of 5 to 30-s (Tables 4.2 & 4.3). However, there were *unclear* positional differences as quantified by GPS-derived measures for the longer duration 300 and 600-s epochs (Figure 4.1). Metabolic power consistently estimated higher maximum mean standardised differences between positions when compared to mean speed for both levels of competition and match halves, whilst also estimating larger opposing positional differences to PlayerLoad™ when compared to mean speed (Figures 4.1 & 4.2). As the rolling epoch duration increased from 5 to 600-s, positional differences between backs and forwards decreased (especially for the sub-elite cohort), with an evident divergence of maximum mean movement as measured by accelerometer-derived PlayerLoad™ when compared to GPS-derived mean speed and metabolic power post the 30-s epoch for both levels of competition (Figures 4.1 & 4.2). Elite forwards produced *very likely* greater maximum mean PlayerLoad™ compared to the backs (moderate effects) for longer epoch durations of 120 to 600-s across both match halves (Figure 4.2 & Table 4.4). Conversely, for the same epoch durations (120 to 600-s) the maximum means for GPS-derived measures of mean speed and metabolic power were *likely* to *most likely* higher for the backs compared to the forwards (Tables 4.2 & 4.3). Sub-elite forwards produced *likely* to *very likely* greater PlayerLoad™ compared to the backs for the 300 and 600-s epochs (small to large effects), compared to mostly *unclear* positional differences as quantified by GPS-derived measures (Figure 4.1 & Table 4.4)

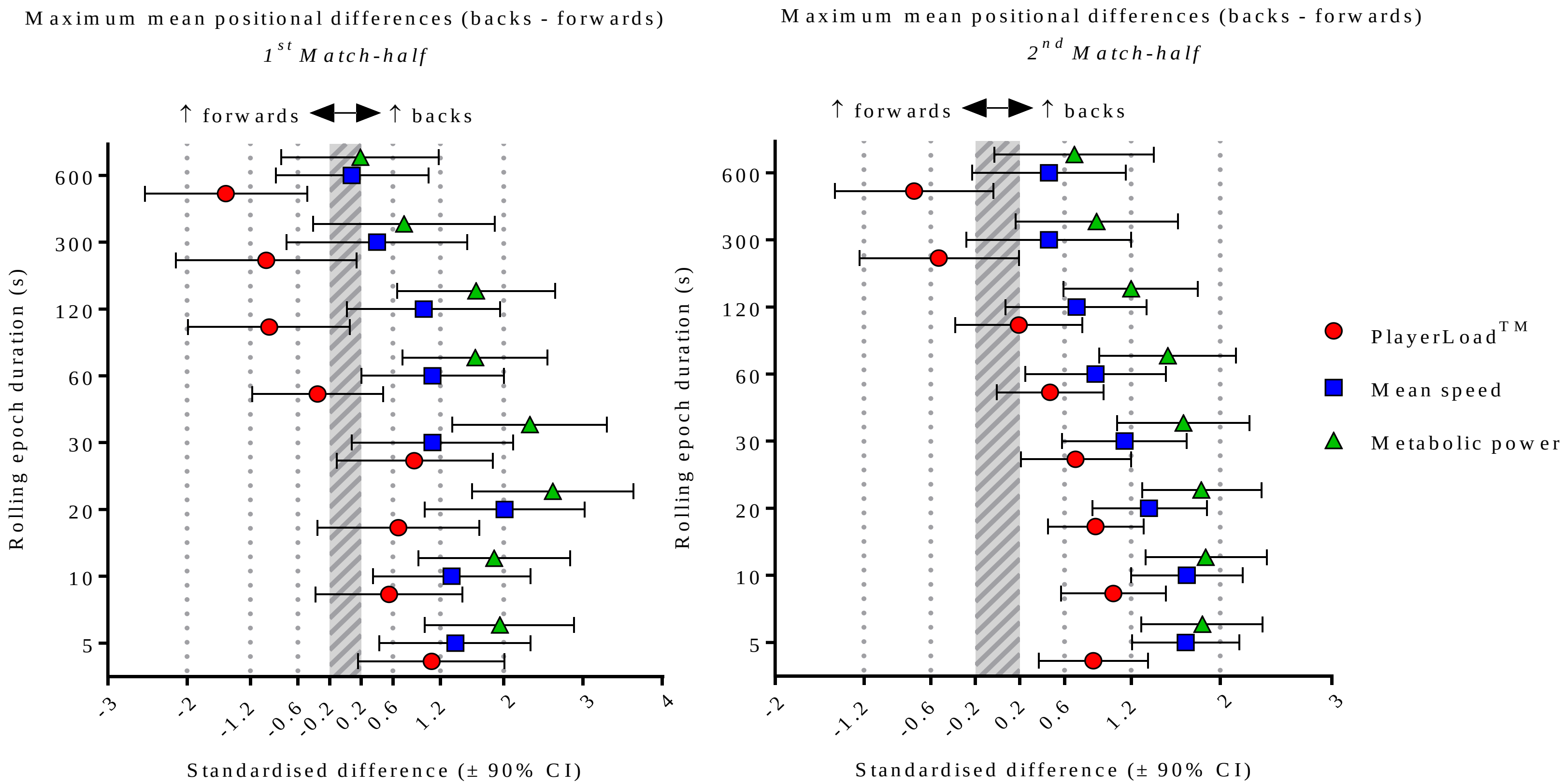

Figure 4.1 Sub-elite (National Rugby Championship) maximum mean standardised positional differences (backs – forwards) for rolling epoch durations of 5 to 600-s by match-half (1st and 2nd match halves).

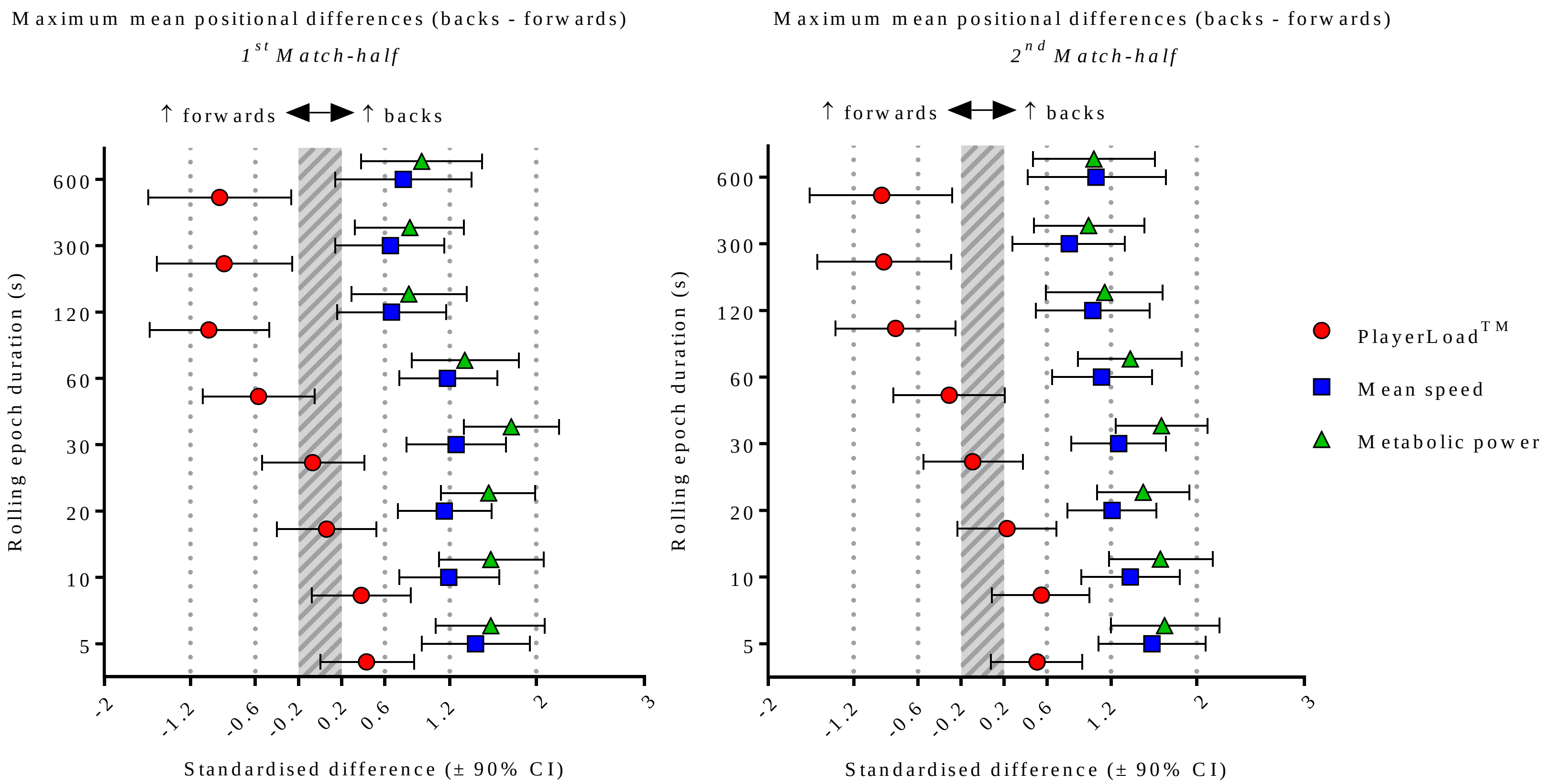

Figure 4.2 Elite (Super 15 rugby) maximum mean standardised positional differences (backs – forwards) for rolling epoch durations of 5 to 600-s by match-half (1st and 2nd match halves).

4.3.5 Match-Half Changes in Maximum Mean Movement

Sub-elite match-half declines in maximum mean movement were more adequately quantified with accelerometer-derived PlayerLoad™ when compared to either GPS measure, with clearer and larger effects for epoch durations ≥60-s (Figure 4.3). For example, sub-elite forwards had large reductions in PlayerLoad™ during the 2nd match-half for epoch durations ≥60-s, whilst mean speed and metabolic power half changes were mostly *unclear* across comparable durations (Figure 4.3, panel A and Table 4.4). Sub-elite match-half changes were mostly *unclear* for all measures and both positions for epoch durations of 5 to 30-s (Figure 4.3). Conversely during elite match-play, GPS-derived measures quantified larger and clearer 2nd match-half declines in maximum mean movement than accelerometer-derived PlayerLoad™ (Figure 4.4). PlayerLoad™ displayed trivial or *unclear* match-half changes for both positions and across all epoch durations during elite match-play (Figure 4.4). Maximum mean metabolic power and mean speed generally declined in the 2nd match-half by a small to moderate standardised extent, with the longer duration epochs of 300 and 600-s displaying the largest 2nd match-half declines (Figure 4.4). Reductions in 2nd match-half maximum mean movement were more evident for forwards than for backs for longer duration epochs during both sub-elite (≥60-s) and elite (≥300-s) match-play (Figures 4.3 & 4.4).

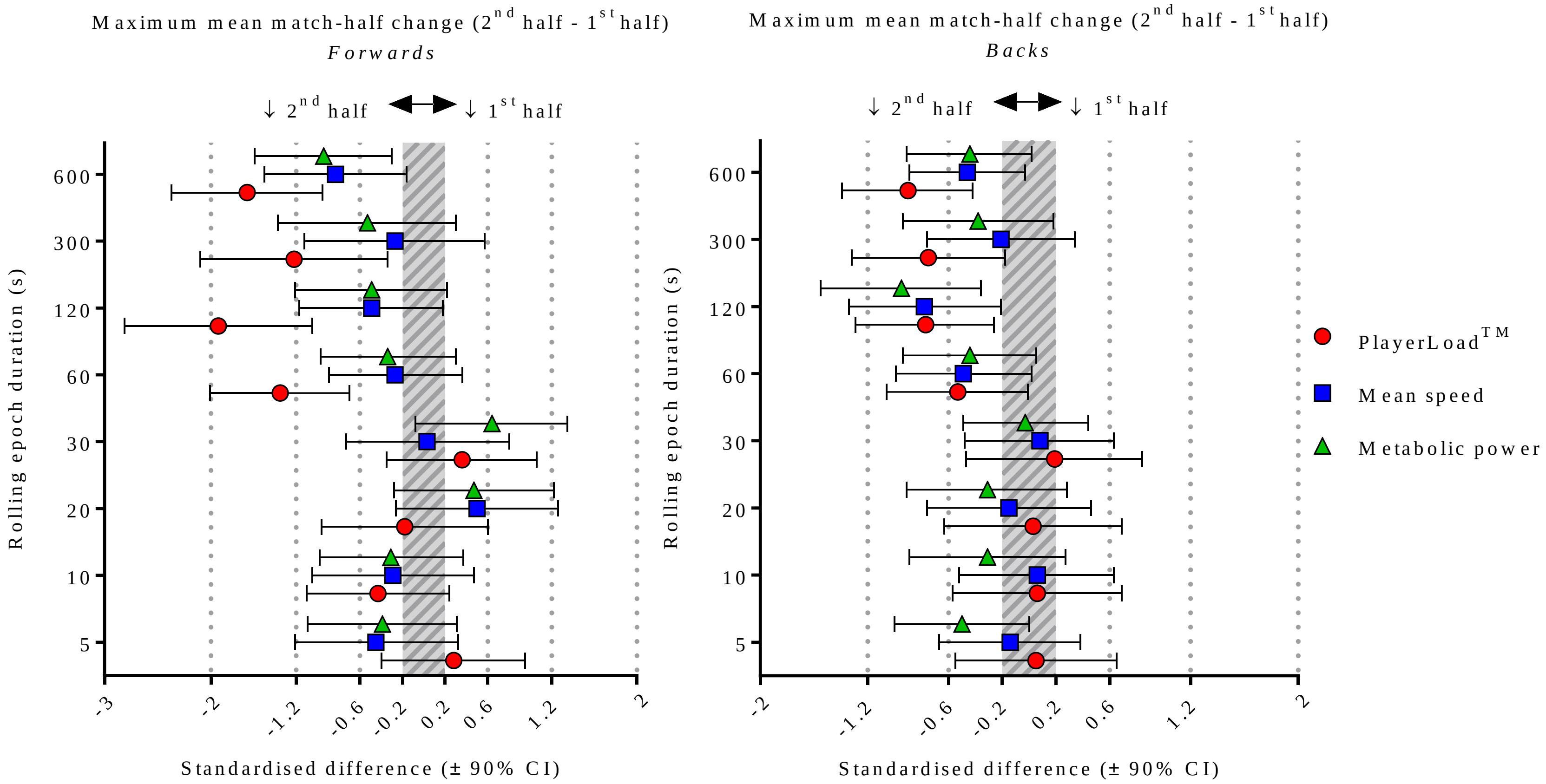

Figure 4.3 Sub-elite (National Rugby Championship) maximum mean match-half standardised changes (2nd match-half - 1st match-half) for rolling epoch durations of 5 to 600-s by position (forwards and backs).

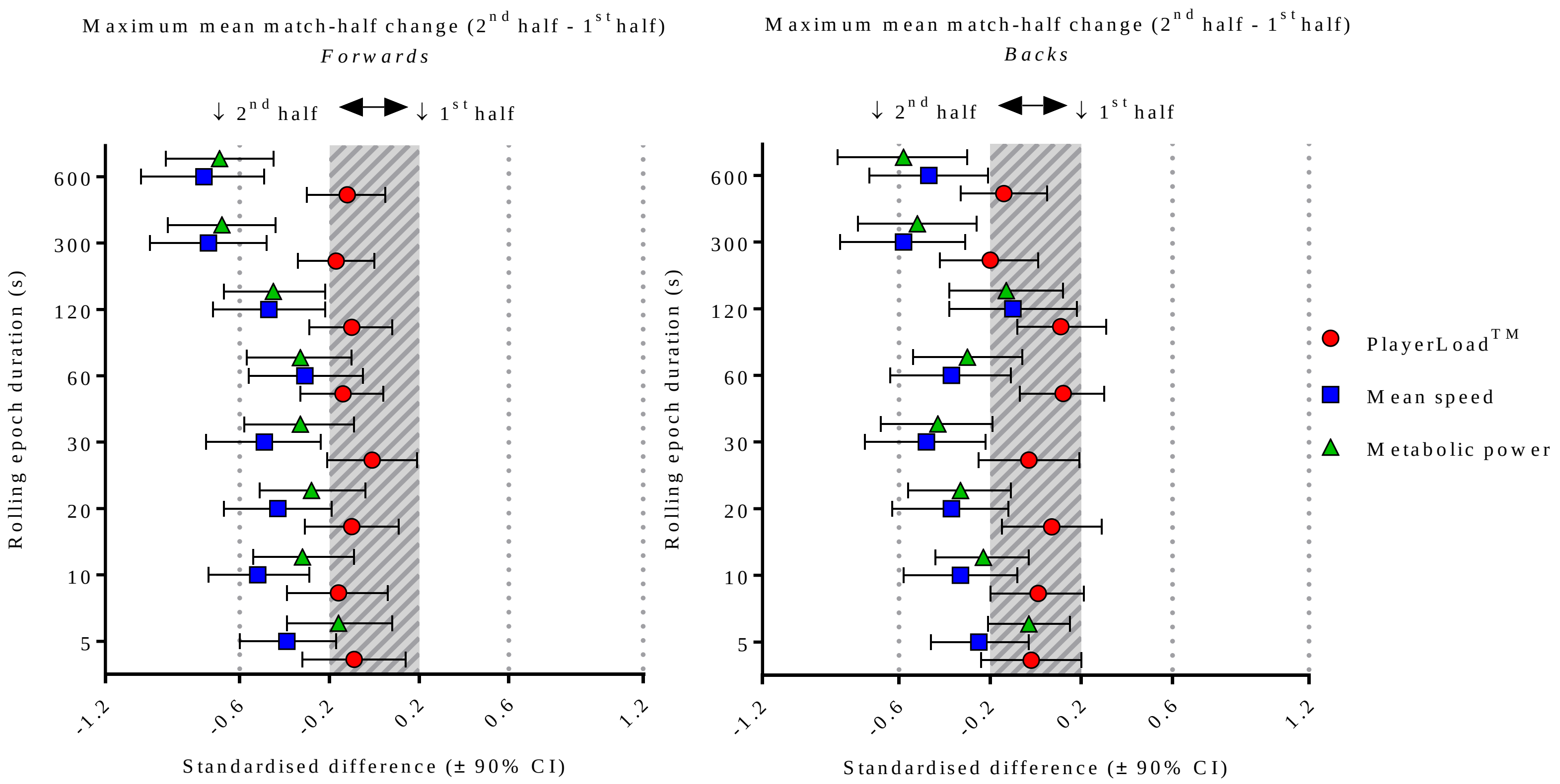

Figure 4.4 Elite (Super 15 rugby) maximum mean match-half standardised changes (2nd match-half - 1st match-half) for rolling epoch durations of 5 to 600-s by position (forwards and backs).

4.4 Discussion

Several key and novel findings were observed: (1) Both GPS- and accelerometer-derived measures had poor sensitivity for quantifying rugby union maximum mean movement of 5 to 600-s; (2) To obtain adequate precision for assessing individual differences or changes in maximum mean rugby union match movement, practitioners require ~ 16 full matches of player movement data (approximate length of a team sport season); (3) Maximum mean movement of 5 to 600-s was inherently unreliable, with typically very low to moderate within-match, between-half reliability and between-match, within-half reliability during both elite and sub-elite match-play across all measures; (4) All measures displayed convergent validity by quantifying similar movement differences between playing positions and match halves to previous rugby union time-motion analyses; (5) Relative to the backs, forwards had greater PlayerLoad^{TM} per unit of distance covered or metabolic power across all rolling epochs during both elite and sub-elite rugby union match-play; (6) Backs produced clearly greater maximum mean speed and metabolic power compared to forwards for all epoch durations for elites, and all epochs except for 300 and 600-s for sub-elites; (7) Elite and sub-elite forwards produced clearly greater maximum mean PlayerLoad^{TM} than backs during longer (≥300-s) epoch durations; (8) Larger 2nd match-half declines in maximum mean movement were evident as epoch duration increased, with greater declines for forwards than backs; (9) Maximum mean PlayerLoad^{TM}, mean speed and metabolic power of 5 to 600-s was of substantially higher intensity than previously reported rugby union whole-period match averages; and (10) Rolling epoch analysis of less than 1-minute (i.e., 5, 10, 20, 30-s) provided useful data that may inform high-intensity interval training prescription and monitoring. The remainder of the discussion focusses on interpretation and application of our findings in the context of others.

4.4.1 Sensitivity of Measures

Both GPS- and accelerometer-derived measures had poor sensitivity for quantifying athlete movement during the most intense passages of rugby union match-play. A professional rugby union athlete's maximum mean movement of 5 to 600-s during match-play will vary on average from measurement to measurement by ~ 11% (mean range; 8 to 14%). This typical error of measurement or noise represents the error that practitioners must contend with when assessing individual differences or changes in athlete movement. The noise (~ 11%) can then be compared to smallest worthwhile change or signal (mean SWD of 2.5%) to calculate the number of repeated measurements required to attain adequate precision of estimates. If signal equal to the noise was deemed acceptable precision by a practitioner, then using the present data as an example, approximately 16 measurements (16 match halves or 8 total matches) would be required to reduce the noise 4 fold to ~ 2.5%. However, for more adequate precision of estimates ideally the noise should be half that of the signal (Hopkins, 2015). Thus practitioners of professional rugby union athletes require ~ 32 match-half measurements or ~ 16 full matches of player movement data (approximate length of a team sport season) to obtain adequate precision (i.e., noise half that of the signal) for assessing individual differences or changes in maximum mean match movement of 5 to 600-s. Hopefully in the future more researchers report the sensitivity of investigated external load measures to inform practitioners on the number of measurements required to accurately interpret and confidently act on movement data.

4.4.2 Reliability of Measures

Rugby union maximum mean movement of 5 to 600-s was inherently unreliable, with typically low to very low within-match, between-half reliability and between-match, within-half reliability during both elite and sub-elite match-play across all measures (ICC; <0.50). Similarly, in English Championship professional rugby union matches, within- and between-player variability of high-intensity activity was large whilst player "match load" variables such as PlayerLoad™ provided a more stable measure of between-match player movement with a coefficient of variation of ~ 10% (McLaren et al., 2015). In agreement, maximum mean PlayerLoad™ displayed improved between-match, within-half reliability (moderate to high) when compared to either mean speed or metabolic power (low) as epoch duration increased past 60-s during elite rugby union match-play (up to ICC; 0.8). PlayerLoad™ may therefore be a more reliable and stable measure of external load than mean speed or metabolic power for monitoring elite rugby union athletes during longer training drills or match bouts (e.g., match-half or whole match).

Present data provides further evidence that reliability of team sport movement as measured by both GPS and accelerometers is inversely related to speed of movement. This finding creates a dilemma for practitioners when selecting measures and is in accordance with the suggestion that validity and reliability of a measure is likely inversely related to its importance for external load quantification and monitoring (Akenhead et al., 2016; Buchheit et al., 2017). Low measure reliability does not mean that PlayerLoad™, mean speed and metabolic power should not be used in the context of quantifying and monitoring maximum mean movement, but rather suggests that more caution is needed when interpreting individual differences or changes. Defining a larger and more conservative SWD (Buchheit, 2016) and/or having more repeated measures are possible solutions to this dilemma, as highlighted by poor measure sensitivity and correspondingly low reliability findings in the present investigation.

4.4.3 Playing Position Differences in Maximum Mean Movement

As expected, GPS was unable to quantify all forms of external load experienced by elite and sub-elite rugby union athletes during the most intense periods of match-play, particularly underestimating external load of the forwards. Forwards are primarily responsible for engaging in contests for possession involving contact such as scrums, lineouts, rucks, mauls and tackles, whilst backs are primarily tasked with trying to gain territory and score points (Quarrie et al., 2013). Compared to rugby union backs, forwards have increased frequency of impacts (Lindsay et al., 2015), "static" exercise bouts (i.e., scrums, rucks & mauls) and durations of "static" bouts (Roberts et al., 2008). During competition forwards also produce greater mean acceleration than backs (Lacome et al., 2013) and "aggregated accelerometer body demands" (Owen et al., 2015). Accelerometer-derived PlayerLoad™ findings corroborate with rugby union time-motion analysis positional movement differences, demonstrating the convergent validity of accelerometers to quantify many frequently occurring rugby union movements that are underestimated by GPS. If the present rolling epoch analysis findings of 5 to 600-s were to be extrapolated in duration to well beyond 600-s (e.g., 40-min match-half) that typically occurs in practice, then the gradual accumulation of many sport-specific and collision-based movements that incur little horizontal displacement over time would likely result in further underestimation of external load via the sole use of GPS. Practitioners should use accelerometers alongside GPS to more adequately quantify, monitor and prescribe totality of athlete movement (external load) during collision-based team sports such as rugby union.

Over shorter exercise bout durations, backs produced greater intensity of movement than forwards. Elite backs produced greater mean speed and metabolic power compared to forwards for all durations of 5 to 600-s (ES >0.60), with similar results for the sub-elite cohort with exception of the 300 and 600-s yielding unclear positional differences. Consistent with present findings, outside backs and half-backs cover greater peak relative running distances than tight 5 forwards (front row and locks, ES >0.60) for rolling average durations of 1 to 10-mins (Delaney et al., 2016d). Facilitating back's ability to produce higher peak running intensities during match-play is greater recovery time to regenerate energy stores between efforts compared to forwards, with a mean exercise: rest ratio of 1: 8.5 vs 1: 6.5 respectively. Increased rest time between efforts is largely due to forwards spending ~ 33% of their time exercising throughout a match completing "static" movements (e.g., scrums, rucks and mauls) compared to ~ 8% for backs (Lacome et al., 2013). Relative to forwards, backs complete a greater frequency of accelerations and decelarations (Owen et al., 2015), contributing to *likely* greater metabolic power for outside backs and half-backs when compared to the tight 5 (ES range; 0.86 to 0.99) (Delaney et al., 2016d). These findings are not surprising considering backs are required to evade opponents with rapid acceleration, change of direction and/or maximal speed to score tries or chase down and tackle opponents to deny try scoring, but do highlight the need for position specific training prescription and monitoring. Practitioners may alter the playing area, number of players, rules and the duration of small-sided games to modify the frequency and intensity of player movements to achieve desired position-specific activity profiles. For example, larger small-sided game playing areas with less players will facilitate more high-speed running whilst smaller playing areas with more players will facilitate more acceleratory, change of direction and collision-based movements.

When compared to the current Super 15 Rugby cohort findings, international rugby union players cover more distance yet accelerate less during the most intense periods of competition (Delaney et al., 2016d). International test-match players thus may complete a greater amount of “constant” speed running compared to Super 15 players, who run at a lower mean speed, yet accelerate more during maximum mean periods of activity as reflected by the increased metabolic power production. Super 15 mean speeds may be comparably lower than test-match rugby because our analysis provided a maximum value for each match-half, whilst the test-match analysis produced one maximum value from the entire match (Delaney et al., 2016d). Maximum mean movement differences between investigations may also be attributed to level of competition, team and opposition playing styles, technologies used (Catapult Optimeye S5 vs GPSports SPI HPU receivers) and statistical analyses performed (e.g., fixed and random effects within model, data inclusion/exclusion criteria etc.). Movement comparisions between levels of competition may help performance staff to prescribe competition level match-specific training intensities to their athletes who are “handed-over” from professional club to national team environments and vice-versa.

Findings provide some evidence to support the convergent validity of mean speed and metabolic power for quantifying positional differences during the most intense periods of elite and sub-elite rugby union match-play. Mean speed and metabolic power positional differences of this study are in agreement with prior rugby union investigations (Delaney et al., 2016d), positional playing roles, and the metabolic power theoretical model accounting for both velocity and acceleration based events. Present findings help to improve limited understanding of position- and duration-specific peak energy expenditures of professional rugby union competition. However, many limitations of the metabolic power method for estimating energy cost during intermittent team sport movement are acknowledged. Metabolic power grossly underestimates movement during shuttle running by 13 to 16% (Stevens et al., 2014b), a soccer-specific circuit by 29% (Buchheit et al., 2015), a generalised team sport circuit by ~ 44% (Brown et al., 2016) and a rugby-specific circuit by ~ 45% (Highton et al., 2016), underpinning its lack of criterion validity versus portable gas analysers. Given metabolic power's sensitivity and reliability to quantify movement differences was no better than the other investigated measures, metabolic power data ($W.kg^{-1}$) are hard to prescribe team sport training from, and many poor criterion validity findings from previous literature, caution with its use is advised.

4.4.4 Match-Half Changes in Maximum Mean Movement

Present findings suggest that professional rugby union athletes preserve their ability to complete maximal intensity movement over shorter durations (≤30-s) across match halves by reducing the amount of movement they perform at lower relative intensities. Similar declines in lower relative intensity cruising and striding distances have been reported as match-half duration progresses and between match halves during rugby union competition (Jones et al., 2015). Reduced running "performance" across the course of a match has been proposed to broadly identify physiological impairment of a player, suggestive of acute fatigue (Mohr et al., 2005). Gradual declines in running intensity throughout match-play are suggestive of players adopting a "slow-positive" pacing profile, common amongst many team sport activity profiles (Waldron et al., 2014). Whilst longer duration efforts of lower relative intensity generally declined in the 2nd match-half (up to 12%), efforts of shorter duration and higher relative intensity (≤30-s) exhibited trivial or small match-half reductions. The lack of decline in very high-intensity rugby union movement between halves is similar to other elite rugby union time-motion analysis findings reporting "no change" in work-to-rest ratios (Lacome et al., 2013) and high-intensity running (Roberts et al., 2008) between halves. Equally, high-intensity movements (high-intensity running, sprinting, maximal accelerations, repeated high-intensity efforts and contacts) did not substantially decrease between halves during professional rugby union as quantified by GPS and integrated inertial sensors (Jones et al., 2015). Consensus on match-half changes in very high-intensity movement between our findings and other investigations across both GPS and accelerometer measures and within both elite and sub-elite rugby union competition demonstrates that the investigated wearable technology measures display convergent validity in measuring what they "ought" to measure. Duration- and position-specific match-half change data may improve our understanding of athlete pacing strategies and this information may then be used to inform substitution/rotation decisions.

4.4.5 Relationship between Accelerometer and GPS Measures

It was clear from the pattern of positional differences across epoch durations and levels of competition that GPS and accelerometer measures provided different information about rugby union player movement. These findings demonstrate that use of either GPS or accelerometers in isolation is inadequate to accurately quantify all forms of rugby union external load. Findings of this investigation support a recent training load monitoring framework for team sports that separates physiological and biomechanical load-adaptation pathways (Vanrenterghem et al., 2017). This framework uses an analogy of a car to describe the physiological vs biomechanical external load that team sport athletes experience. The physiological load component can be viewed as a car engine with GPS time, distance and speed derivatives providing an estimate of "fuel" in the player's "engine", facilitating monitoring of external work to estimate internal energy demands or metabolic load (e.g., glycogen depletion, heart rate). Whereas biomechanical load refers to external work performed by the body's soft tissues (e.g., muscles, bones and ligaments, analogous to a car's suspension) against the ground and other player's during impact, that can be estimated in the field with highly responsive motion sensors such as accelerometers.

PlayerLoad™ has strong positive correlations with total distance in Australian Rules Football [r = 0.63 to 0.76; (Boyd et al., 2010) and r = 0.90; (Aughey, 2011)], and is mainly derived from vertical axis accelerations (44.1% ± 2.5%) during Australian Rules Football match-play (Cormack et al., 2013) and treadmill running (55.7% ± 5.3%) (Barrett et al., 2014). These results make intuitive sense as team sport athletes run great distances leading to a high frequency of propulsive and braking forces against the ground that are quantified by accelerometers as vertical accelerations accumulated over time. Variations in physiological and biomechanical loads are generally experienced together (Vanrenterghem et al., 2017), hence why total distance and PlayerLoad™ often correlate. Present results indicate that neither accelerometer nor GPS measures should be used as a proxy measure for the other when attempting to quantify the most intense periods of collision-based team sport match-play as whether they are correlated or not, they clearly measure different constructs. Furthermore, the common use of total distance as a proxy measure of overall training and/or match volume (Buchheit et al.,

2017) should be undertaken with caution and is not advised when monitoring and prescribing rugby union athlete external training loads. If practitioners want to understand both the physiological and biomechanical external loads of their athletes for informing subsequent recovery and training design, both GPS and accelerometers should be used.

No research using optical or local positioning systems to quantify player movement has utilised the methodological approach outlined in the present study, although this could be easily achieved in future investigations. All that would be required are player positional x and y coordinates for these alternate player tracking solutions to calculate distance, velocity, acceleration and subsequently replicate mean speed and metabolic power measures we used. Global positioning systems may calculate velocity via positional differentiation (change in receiver location with each satellite signal) or using the Doppler-shift method (change in frequency in the satellite signal). Most GPS manufacturers now use the Doppler-shift method as it has been reported to have greater precision and reduced measurement error (Townshend et al., 2008) when compared to deriving velocity via distance over time calculations that optical and local positioning systems use. Another key advantage of wearable systems is the 3-dimensional (x, y and z) quantification of athletic movement via integrated accelerometry, highlighted by present findings suggesting that athlete external loads will be underestimated if only movement in x and y coordinates are measured, making intuitive sense.

4.4.6 Implications for Training Prescription

The most intense periods of rugby union match-play were of substantially higher intensity than previously reported whole-period match averages. For example, Super 15 rugby union forwards and backs produced match mean speeds of 56.1 and 68.7

m.min^{-1} respectively (McLellan et al., 2013). These whole match mean speed numbers are lower than the longest epoch duration (600-s) maximum means of elite Super 15 forwards (72.3 m.min^{-1}) and backs (79.1 m.min^{-1}) (Table 4.2). Grand mean speed reached 155 m.min^{-1} during the maximum mean 60-s epoch and 380 m.min^{-1} during the most intense 5-s epoch (Table 4.2). Similar stark discrepancies between movement intensities can be observed when comparing the 5 to 600-s maximum means of PlayerLoad™ and metabolic power herein compared to previous rugby union investigations quantifying whole-period averages. Current data illustrates that if professional rugby union training is prescribed relative to the average activity profile of a match, players will be under-prepared for the most intense periods or worst-case scenarios of match-play.

Not surpringly, present data indicate that as exercise duration increases, intensity of rugby union match movement declines. The declines in movement are non-linear and logarithmic in nature, with this intensity-duration physiological relationship often referred to as the power law relationship (Delaney et al., 2017b). The power law relationship will be further explored in Chapter 7, however for the purpose of the present investigation it was clear that although there are many complex interactions between central and peripheral fatigue (either transient and/or accumulated) and numerous contextual match factors inherent within team sports, movement duration is still very predictive of movement intensity. Subsequently, practitioners may use mathematical modelling of the power law relationship to predict movement intensity over a range of durations outside of those collected by wearable technology with reasonable accuracy, enabling practitioners to prescribe training that is more specific to the physiological and biomechanical rigors of competition.

4.5 Strengths, Limitations & Future Directions

Whilst this investigation provides many novel and meaningful insights that may aid coaching and performance staff in quantifying, monitoring and prescribing athlete external loads, there are limitations that need to be acknowledged. Positional analyses were limited to positional forward and back packs rather than more specific playing positions (e.g., prop, centre, scrum-half) to increase precision of estimates and to first assess if the respective technologies were sensitive enough to quantify broader positional classifications prior to comparing specific positional groupings. The case study nature of the present study may be considered a limitation and whilst two professional teams of two competitive levels with many repeated measures were included, league-wide investigations with opposition analyses is the way forward to better understand collision-based team sport activity profiles. It is acknowledged that placement of an accelerometer to the trunk is only an estimate of whole-body accelerations that is far from perfect, although offers a starting point for biomechanical load estimation in the field. Future research should continue to investigate the influence of sensor location, sensor harnessing and relationships between segmental and whole-body acceleration. Further, whether these intense periods of match-play have any bearing on individual and/or team key performance indicators and/or match outcome is unclear. Understanding of player movement immediately following these maximum mean periods of activity is also limited and may provide valuable insights on player pacing strategies and accumulated or transient fatigue that may inform real-time player substitution or rotation decisions. Altogether, knowledge of the strengths and limitations of the technologies and the measures they provide is crucial for both practitioners and researchers alike to accurately interpret the external load data produced and subsequently provide recommendations for action to influence the training process.

4.7 Practical Applications

- Professional rugby union player movement needs to be monitored across many matches to obtain adequate precision for assessing individuals during intense periods of match-play.
- Accelerometers should be used in addition to GPS to quantify, monitor and prescribe player movement in rugby union and other collision-based team sports.
- Neither accelerometer nor GPS measures should be used a proxy measure for the other, as they measure different external load constructs (biomechanical and physiological load respectively).
- Duration- and position-specific player movement data derived from wearable technologies and rolling epoch analyses may be used as a reference for training monitoring and prescription to objectively prepare players for the most intense periods of competition. For example, small-sided games may be modified (pitch size, number of players, rules, verbal encouragement) to achieve desired duration- and position-specific physiological and biomechanical external loads whilst simultaneously training technical and tactical skills.
- Given metabolic power's sensitivity and reliability to quantify movement differences was no better than the other investigated measures, and metabolic power data are hard to prescribe team sport training from, we advise caution with its use.

4.8 Conclusions

The poor sensitivity and low reliability of GPS and accelerometer measures of maximum mean movement imply that rugby union players need to be monitored across many matches to obtain adequate precision for assessing individuals. Although all measures displayed convergent validity, accelerometers provided meaningful information additional to that of GPS. It is recommended that practitioners use accelerometers alongside GPS to quantify, monitor and prescribe player movement in rugby union and other collision-based team sports.

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CHAPTER 5: STUDY 3 – FACTORS INFLUENCING THE PEAK INTENSITIES OF ELITE AND SUB-ELITE RUGBY UNION COMPETITION

5.1 Introduction

Collison-based team sports such as rugby union are characterised by low-intensity activity interspersed with frequent bouts of high-intensity activity (Duthie et al., 2003). If rugby union training is prescribed relative to the average activity profile of a match, players will likely be underprepared for the most intense periods of match-play (Delaney et al., 2016d). Despite the majority of team sport competition being spent at submaximal intensity, high-intensity activities are often aligned with key events that determine match outcome (Faude et al., 2012; Gabbett et al., 2016). For example, in rugby league 56.1% of 2083 repeated high-intensity efforts (1169) occurred within 5minutes of either scoring or defending a try during 21 semi-professional matches across 11 teams (Gabbett et al., 2016). Similarly, 83% of 360 goals scored in professional soccer were preceded by at least one powerful physical action of the scoring or the assisting player, with straight line sprinting the most frequent action prior to goal scoring (Faude et al., 2012). These results signify the importance of physically conditioning football athletes for high-intensity passages of competition.

There is limited research using accelerometers to quantify the most intense periods of football competition, which is surprising given the reduced accuracy of GPS for quantifying high-velocity and acceleratory movements that frequently occur (Boyd et al., 2013; Jennings et al., 2010; Rawstorn et al., 2014). In a recent systematic review investigating the use of microtechnology to quantify the peak match demands of football codes (Whitehead et al., 2018b), only 2 of the 27 included studies used accelerometer-derived metrics such as PlayerLoad^{TM}, whilst GPS-derived relative distance was reported in 63% of studies. Clearly, there is a need to examine the efficacy of accelerometers to quantify and characterise intense passages of football competition.

Activity profile analyses have evolved substantially over the past 30 years, due largely to technological and methodological advances. Analyses have evolved from reporting whole match movement values (Edgecomb et al., 2006), to segmenting movement completed into discrete match periods (e.g. halves, quarters, rotations) (Aughey, 2010; Duthie et al., 2005), to movement relative to time on field (Coutts et al., 2010b; Varley et al., 2013b), to movement within pre-defined periods of matches (Jones et al., 2015) and more recently, to movement within rolling average time periods (Delaney et al., 2016d; Varley et al., 2012a). The segmentation of player movements into discrete periods allows practitioners to detect fluctuations in player movement (i.e. peaks and troughs), that is not possible with whole match values. A better understanding of within-match fluctuations in player movement may enable practitioners to prescribe training that is more representative of the rigors of competition.

The most intense periods of football competition do not fall completely within pre-defined periods of time and therefore likely underestimate peak periods and overestimate subsequent periods of activity (Varley et al., 2012a). Pre-defined time-motion analysis using wearable GPS technology found peak 5minute high-velocity ($\geq$ 4.17 $m.s^{-1}$ or $\geq$ 15 $km.h^{-1}$) distance covered during football matches was underestimated by up to 25% whilst overestimating subsequent periods of activity by up to 31%

compared with rolling periods (5 minute average from every time point) (Varley et al., 2012a). The decrement in player distance covered between the peak and the following period was also up to 52% greater using rolling compared to pre-defined periods. Subsequently, practitioners should use rolling average epochs when attempting to accurately identify and quantify peak periods of player movement and periods thereafter during competition (Cunningham et al., 2018; Ferraday et al., 2020; Varley et al., 2012a).

Duration- and/or position-specific player movement differences have been observed during the most intense periods of match-play across various football codes including: rugby sevens (Couderc et al., 2017; Furlan et al., 2015; Murray et al., 2015), rugby league (Delaney et al., 2016a; Delaney et al., 2015; Kempton et al., 2015b; Whitehead et al., 2018a), rugby union Chapter 3, (Carling et al., 2017; Delaney et al., 2016d; Read et al., 2018b) Australian Rules Football (Black et al., 2016; Delaney et al., 2017a), Gaelic football (Malone et al., 2017b) and soccer (Delaney et al., 2017b; Ferraday et al., 2020; Sparks et al., 2016; Trewin et al., 2018; Varley et al., 2012a). These investigations amongst others have provided valuable insights into the highly intermittent nature of team sport movement and highlighted that rolling time-motion analyses may assist practitioners in the design, prescription and monitoring of training that is more representative and specific to competition. Yet many factors that may influence player movement during the most intense periods of football competition are poorly understood, and deserve further investigation.

Little is known about how time on field influences player peak intensities, how these peak periods of activity change across the course of a season, or if differences exist between match-halves or between levels of competition. There is a paucity of research investigating the use of accelerometers to measure the peak intensities or worst-case scenarios of competition, with GPS measures of relative distance and metabolic power predominating the player tracking literature. Further, only two studies to date (Read et al., 2018b; Whitehead et al., 2018a) have utilised rolling average epochs of less than 1 minute, with neither investigating professional rugby union athletes. Subsequently, the present investigation aimed to quantify and characterise the most intense periods of rugby union competition within and between individuals, examining factors that may influence peak intensities, such as: a) epoch durations of 5 to 600s, b) playing positions, c) match-halves, d) levels of competition, e) within-season trends, f) time on field and g) match-time the peak occurred.

5.2 Methods

This study extends on Chapter 4, with the study design, participants, equipment and data collection, measures of maximum mean (peak intensity) and data filtering and processing procedures all previously established (Chapter 4, methods). Consequently, this chapter will focus on novel statistical analyses that enable the quantification and characterisation of peak intensities of elite and sub-elite rugby union.

5.2.1 Statistical Analyses

All measures were analysed with two general linear mixed modelling procedures (Proc Mixed) in SAS (detailed in Chapter 4) and log-transformed to reduce non-uniformity of error (Hopkins et al., 2009). The first mixed model provided the four means and standard deviations of the positions and the match-halves shown in Figures 5.1 and Figure 5.2; this model also provided the harmonic mean of the four standard deviations, which is an appropriate mean standard deviation for assessing magnitudes of effects via standardisation (Hopkins, 2007b). The model included a simple linear numeric fixed effect for calendar date interacted with playing position (to estimate a separate within-season trend for each position averaged across the halves). The second model provided magnitude-based decisions about the differences and changes in the means; in this model, mean time on the field for each player in each half was re-scaled to zero to avoid adjusting the peak intensities to a grand mean time on the field for positions and halves. This re-scaling enabled better quantification of positional (forwards vs backs) and match-half (1^{st} half vs 2^{nd} half) mean differences. The magnitude of the effect of time on the field was also evaluated by standardising the change in the peak measure corresponding to two within-player standard deviations for each playing position and match-half (Hopkins et al., 2009). Comparisons of peak movement between elite and sub-elite levels of rugby competition were made using a spreadsheet for combining outcomes from several subject groups (Hopkins, 2006). The time in each half when the peak intensity occurred (defined by the mid point of the rolling-average window) was summarised with means and standard deviations.

The magnitudes of effects (positional differences or match-half changes in means; standard deviations derived from random effects) were evaluated by standardisation, which was performed by dividing each effect by the between-player standard deviation in a typical match to provide the effect size (ES). This standard deviation was derived by adding the variances for the random effects for player identity and the residual. The smallest worthwhile difference (SWD) or change in means is 0.2 standard deviations; thresholds for moderate, large and very large differences are 0.6, 1.2 and 2.0, respectively (Hopkins et al., 2009). Thresholds for evaluating standard deviations (derived by taking square roots of random-effect variances) were half these values

(Smith et al., 2011). Uncertainty in effects was expressed as 90% compatibility limits or intervals and as probabilities that the true effect was substantially positive and negative. These probabilities were used to make a qualitative probabilistic non-clinical magnitude-based decisions (MBD) about the true effect (Hopkins et al., 2009): if the probabilities of the effect being substantially positive and negative were both > 5%, the effect was reported as unclear. The scale for interpreting the probabilities was as follows: 25-75%, possible; 75-95%, likely; 95-99.5%, very likely; > 99.5%, most likely (Hopkins et al., 2009).

5.3 Results

5.3.1 Elite Rugby Peak Intensities

Figure 5.1 illustrates the increase in Super 15 Rugby (elite) peak intensity as time decreases across the three measures (mean speed, metabolic power and PlayerLoad^{TM}) by playing position and match-half. Backs produced greater peak mean running speed than forwards across all epoch durations, with moderate (ES ± 99% CI: 0.8 ± 0.5) to large (1.7 ± 0.5) effects (Figure 5.1, top panel). There were small to moderate standardised peak mean speed differences between match-halves (0.3 ± 0.3 to 0.8 ± 0.3). The match-half 'grand' mean speed averaging both positions and half data (i.e. b1, b2, f1, f2 = 65.5, 62.3, 59.4, 55.7 m.min^{-1}) for visual comparison with the peak intensities reached across each epoch duration was 60.7 m.min^{-1} (Figure 5.1, top panel dashed line). Unsurprisingly, all duration- and position-specific peak running speeds produced were substantially higher than the ~ 40 minute rugby union match-half 60.7 m.min^{-1} mean speed (Figure 5.1). Similar findings were observed across all measures and both levels of competition (Figures 5.1 & 5.2).

Elite backs produced greater metabolic power when compared to forwards across all 5 to 600 s epoch durations, ranging from moderate (0.8 ± 0.5) to large (1.7 ± 0.5) effects (Figure 5.1, middle panel). Similarly to mean speed, players of both positions generally produced greater peak metabolic power in the first match-half compared to the second across a range of epoch durations (0.2 ± 0.2 to 0.6 ± 0.2). The match-half 'grand' metabolic power mean averaged across both positions and whole-half data (i.e. b1, b2, f1, f2 = 7.53, 7.15, 6.53, 6.11 $W.kg^{-1}$) for visual comparison with the peak intensities reached across each epoch duration was 6.83 $W.kg^{-1}$ (Figure 5.1, middle panel).

Backs produced greater accelerometer-derived PlayerLoad™ than forwards for very short duration epochs (5 and 10 s), with small (0.4 ± 0.5) to moderate (0.6 ± 0.5) standardised effects (ES ± 99% CI, Figure 5.1, bottom panel). However, as epoch duration increased past 120 s, forwards produced moderately (0.6 ± 0.4 to 0.7 ± 0.4) greater PlayerLoad™ when compared to backs. There was good evidence for trivial or marginally trivial-small changes between halves for both forwards and backs for PlayerLoad except for the two longest epoch durations, where there is a greater likelihood of a small effect (Figure 5.1, bottom panel). The match-half 'grand' PlayerLoad™, averaging both positions and whole-half data (i.e. b1, b2, f1, f2 = 0.46, 0.46, 0.54, 0.52 au) for visual comparison with the peak intensities reached across each epoch duration was 0.5 au (Figure 5.1, bottom panel dashed line).

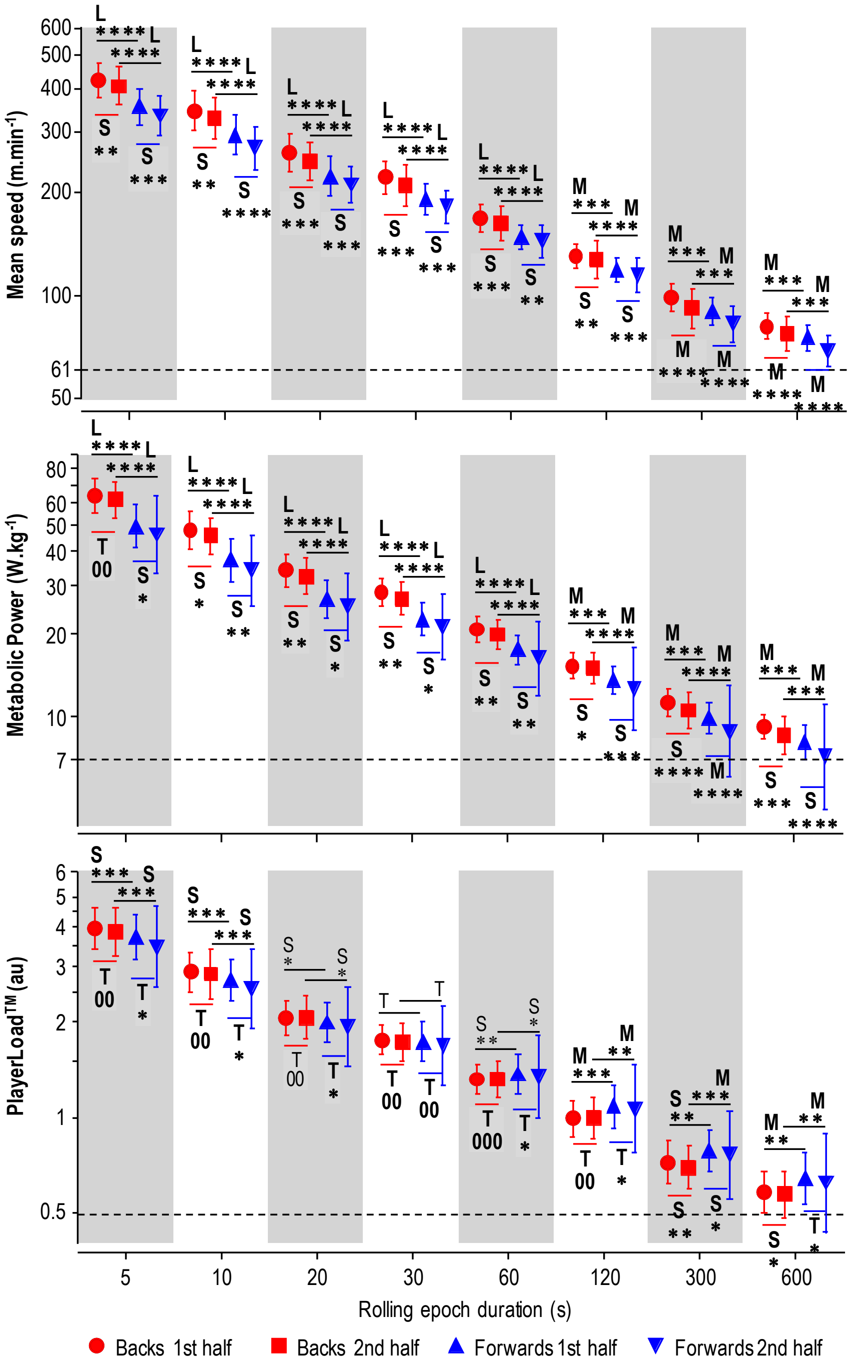

Figure 5.1 Peak-mean speed, metabolic power and PlayerLoad™ for rolling epoch durations of 5 to 600 s during elite rugby competition.

Data presented are means ± SD. Superscripts indicate observed magnitudes as follows: T, Trivial; S, Small; M, Moderate; L, Large; VL, Very Large. Asterisks indicate likelihood of true substantial effects as follows: *possibly, **likely, ***very likely, ****most likely. Superscript zeros indicate likelihood of true trivial effects as follows: ^{00}likely, ^{000}very likely, ^{0000}most likely. T* indicates a possibly trivial, possibly substantial effect. Effects shown in bold have adequate precision with 99% compatibility limits. Effects without asterisks or superscript zeros are unclear (inadequate precision) with 90% compatibility limits. Dashed line = half mean intensity.

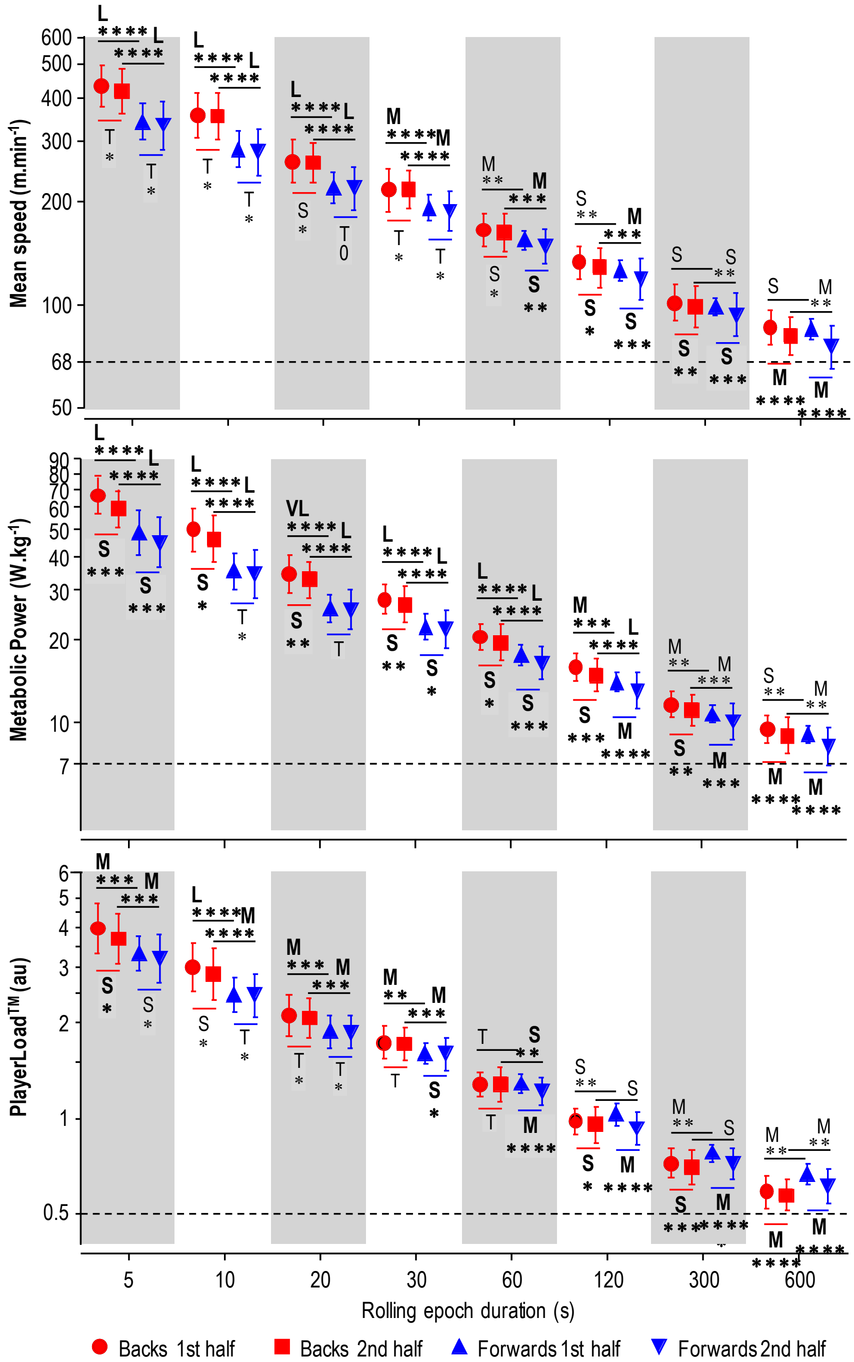

Figure 5.2 Peak-mean speed, metabolic power and PlayerLoad™ for rolling epoch durations of 5 to 600 s during sub-elite rugby competition.

Data are means ± SD. Superscripts indicate observed magnitudes: T, Trivial; S, Small; M, Moderate; L, Large; VL, Very Large. Asterisks indicate likelihood of true substantial effects: *possibly, **likely, ***very likely, ****most likely. Superscript zeros indicate likelihood of true trivial effects: ^{00}likely, ^{000}very likely, ^{0000}most likely. T* indicates a possibly trivial, possibly substantial effect. Effects shown in bold have adequate precision with 99% compatibility limits. Effects without asterisks or superscript zeros are unclear (inadequate precision) with 90% compatibility limits. Dashed line = half mean intensity.

5.3.2 Sub-Elite Peak Intensities

Figure 5.2 illustrates the increase in National Rugby Championship (sub-elite) peak intensity as time decreases across the three maximum mean measures (mean speed, metabolic power and PlayerLoad^{TM}) by playing position and match-half. Backs produced greater peak mean speed compared to forwards for epoch durations of 5 to 120 s, displaying small (0.5 ± 0.6) to large (1.9 ± 0.6) standardised positional differences (Figure 5.2, top panel). Greater peak mean running speed differences were observed between match-halves as epoch duration increased, with moderate (0.6-0.7) standardised differences for both posititons during the peak 600 s epoch (Figure 5.2, top panel). The NRC match-half 'grand' mean speed averaging both positions and half data (i.e. b1, b2, f1, f2 = 71.2, 68.3, 68.3, 64.2 m.min^{-1}) for visual comparison with the peak intensities reached across each epoch duration was 68 m.min^{-1} (Figure 5.2, top panel dashed line).

Peak metabolic power produced was greater for sub-elite backs than forwards for all 5-120 s epoch durations across both match-halves, from a moderate (1.0 ± 0.7) to very large extent (2.4 ± 0.6) (Figure 5.2). Positional differences in peak metabolic power typically decreased as epoch duration increased. Substantial match-half changes in peak metabolic power were of small (0.4 ± 0.4) to moderate (0.7 ± 0.3) magnitude. The match-half 'grand' metabolic power, averaging both positions and whole-half data (i.e. b1, b2, f1, f2 = 7.91, 7.57, 7.26, 6.78 W.kg^{-1}) for visual comparison with the peak intensities reached across each epoch duration was 7.38 W.kg^{-1} (Figure 5.2, middle panel dashed line).

Sub-elite backs generally produced greater accelerometer-derived PlayerLoad^{TM} than forwards for epoch durations of less than 30 s (ES ± 99% CI: 0.8 ± 0.5 to 1.2 ± 0.6),

Figure 5.2, bottom panel). However similarly to the elite cohort, as epoch duration increased beyond 60 s sub-elite forwards produced small to moderate increases in PlayerLoad™ when compared to backs for durations of 120 to 600 s (ES range: 0.5 ± 0.5 to 1.0 ± 0.7)(Figure 5.2). The first match-half had greater peak 60 to 600 s PlayerLoad™ than the second half for both positions (ES range: 0.2 ± 0.3 to 1.1 ± 0.4, Figure 5.2). The National Rugby Championship match-half 'grand' PlayerLoad™ averaging both positions and whole-half data (i.e. b1, b2, f1, f2 = 0.48, 0.47, 0.56, 0.52 au) for visual comparison with the peak intensities reached across each epoch duration was 0.51 au (Figure 5.2, dashed line).

5.3.3 Elite vs. Sub-Elite Peak Intensities of Competition

Of 96 elite (Super 15) vs sub-elite (National Rugby Championship) peak intensity of competition comparisons made across 8 epoch durations (5, 10, 20, 30, 60, 120, 300, 600 s), 2 positions (forwards, backs), 2 match-halves (1st, 2nd) and 3 measures (mean speed, metabolic power and PlayerLoad™), only 25/96 comparisons (26%) found clear peak intensity differences between levels of competition that were greater than the smallest worthwhile difference or change in means (i.e. 0.2 × between-player standard deviation). When partitioned into positional comparisons between levels of competition, 43/48 (90%) of comparisons between backs found no clear elite vs sub-elite differences greater than the SWD. Of the 5 out of 48 (10%) comparisons that were clear and greater than the SWD, peak mean speed was greater for sub-elite than elite backs across a few sporadic epoch durations by match-half. For the forwards, 20/48 level of competition comparisons (42%) were clear and greater than the SWD. Sub-elite forwards produced greater peak mean speed and metabolic power than elite forwards during longer duration epochs (i.e. 300 and 600 s). However, elite forwards produced greater peak PlayerLoad^{TM} than sub-elite forwards across shorter epoch durations (i.e. 5 to 120 s).

5.3.4 Peak Intensity of Competition Within-Season Trends

5.3.4.1 Elite rugby

GPS-derived measures of mean speed and metabolic power displayed mostly trivial and unclear 5 to 600 s peak intensity within-season trends across the Super Rugby season. The largest observed within-season trend was a decline in the peak mean speed attained by the backs in the 600 s epoch during the first match-half, with a moderate decline of 0.7 ± 0.7 (86% likely substantial). Similarly, metabolic power declined within the same 600 s epoch duration during the first match-half to a small extent for the backs over the course of the season 0.4 ± 0.6 (73% possible).

PlayerLoad^{TM} had mostly small within-season trend standardised declines, with shorter duration epochs in the 1st match-half displaying the largest magnitude of decline as the season progressed (i.e. 5 to 30 s decline ranges: backs; -0.4 ± 0.2 to -0.6 ± 0.2 and forwards; -0.3 ± 0.3 to -0.5 ± 0.4), equating to an ~ 6% within-season peak PlayerLoad^{TM} decline.

5.3.4.2 Sub-elite rugby

National Rugby Championship within-season peak movement declined to a greater extent as the epoch duration increased from 5 to 600 s. Declines in peak movement were generally more pronounced for forwards than backs as the season progressed. For the forwards, the 60 and 120 s epochs consistently displayed the largest magnitude of within-season decline across all measures, especially during the 1st match-half (ES range ± 90% CI; -1.4 ± 0.6 to -1.9 ±1.0) equating to a mean large decline of 13 to 15%. Backs in the 2nd match-half displayed increased peak PlayerLoad^{TM} as the season progressed for shorter duration epochs (i.e. 10 to 30 s, ES range ± 90% CI; 0.8 ± 0.4 to 1.2 ± 0.7) equating to a mean increase of 11 to 20%.

5.3.5 Influence of Time on Field on Peak Intensities of Competition

Super 15 and NRC players who were on the field for a longer amount of time (Table 5.1) generally achieved small (ES: ~ 0.2) increases in peak mean speed, metabolic power and PlayerLoad™ than players who were on field for shorter durations. The average time on field (min) during elite rugby competition by position and match-half was (Backs 1st: 43, Backs 2nd: 39 Forwards 1st: 44, Forwards 2nd: 35). Corresponding average time on field for sub-elite players was (Backs 1st: 43, Backs 2nd: 35, Forwards 1st: 43, Forwards 2nd: 33 minutes). Time on field influenced peak intensity to a greater extent in the second match-half compared to the first for both sub-elite and elite rugby competitions. The majority of 5-600 s epoch durations displayed trivial and unclear standardised effects of time on field influencing the peak mean speed, metabolic power and PlayerLoad™ during the first match-half. In contrast, most 5-600 s duration epochs displayed small to moderate standardised (ES range: 0.2-0.6) and percent effects (up to 9% and 11% for NRC and Super 15 competitions respectively) for the influence of time on the field on peak second match-half intensity.

Table 5.1 Within-player standard deviations for time on the field (min) during sub-elite and elite rugby competition.

Position	Half	**Sub-elite Rugby**	**Elite Rugby**
Back	1st	2.4	6.4
Back	2nd	7.6	9.6
Forward	1st	1.9	7.2
Forward	2nd	10.1	8.8

5.3.6 Game Time of Peak Intensity Periods

The most intense 5-600 s passages of elite and sub-elite rugby union competition occurred near the middle of both first and second match-halves. The grand pooled position and match-half game time of peak movement (mean ± SD, averaged across the three variables and all epoch durations) was 23 ± 12 and 21 ± 13 minutes into the match for NRC and Super 15 Rugby matches respectively. Comparing the mean game time that peak periods of intensity occurred (NRC: 23 minutes and Super 15: 21 minutes) with the middle of the match-half durations (NRC: 22 minutes and Super 15: 23 minutes) enables practitioners to understand when these peak periods of competition occur relative to random chance. For example, rugby union has 40-minute halves plus any additional stoppage time, thus the 20 minute mark of each half represents the theoretical point in time that the peak period of activity would occur on average (at the population and not study sample level) by pure chance for a 40 minute half if every minute of the game recorded the same frequency of individual player peaks. The NRC peak periods of intensity occurred on average 53 seconds after the middle of the half and occurred ~ 2 minutes prior to middle of the half during Super 15 competition.

Whilst the peak intensities of competition occurred near the middle of match-halves, the time that they occurred between the first and second half differed. The most intense passages of competition occurred at latter stages in the second match-half when compared to the first. The game time of peak intensity for each position and match-half averaged across all epoch durations and three measures were: (backs 1st; 22.4, backs 2nd; 25.1, forwards 1st; 19.6, forwards 2nd 23.4) for NRC match-play and (backs 1st; 20.5, backs 2nd'; 23.2, forwards 1st; 20.5, forwards 2nd; 21.2) for Super 15 Rugby match-play. Match-half duration including stoppage time for each competition was: NRC (1st;

43.1 ± 1.9, 2nd; 45.3 ± 1.4 minutes) and Super 15 Rugby (1st; 45.5 ± 3.6, 2nd; 46.9 ± 2.8 minutes). When the game time of peak intensity in each half was adjusted for by the duration of the half, peak intensities of 5 to 600 s occurred 1.1 and 2.1 minutes later in the second match-half compared to the first for NRC and Super 15 Rugby respectively. In Super 15 Rugby, the 300 and 600 s peak intensity periods occurred later in the second match-half when compared to the first for both the backs and the forwards (3.8 and 6.9 minutes respectively), when adjusted for differences in match-half duration. During NRC matches, the most intense 60 to 120 seconds of competition displayed the greatest differences between halves, occurring later in the second half compared to the first for both backs (1.5 minutes) and forwards (5.1 minutes).

5.4 Discussion

The present investigation aimed to quantify and characterise the most intense periods of rugby union competition within and between individuals, examining factors that may influence peak intensities, such as: a) epoch duration, b) playing positions, c) match-halves, d) levels of competition, e) within-season trends, f) time on field and g) match-time the peak occurred. The key and novel findings of the present study were: (**1**) Rugby union backs produced greater peak mean speed and metabolic power than forwards during both sub-elite and elite competitions across most durations from 5 to 600 seconds (typically ES > 0.6). (**2**) The peak intensity of matches was typically greater in the first half than the second half (ES > 0.2), across sub-elite and elite rugby competitions for durations of 60 seconds and beyond. (**3**) The majority (74%) of 96 comparisons made between the most intense periods of elite versus sub-elite rugby competition yielded unclear or trivial differences, irrespective of duration, position, match-half or the measure used. Of the remaining 26%, there were more clear differences > SWD for forwards than backs. (**4**) Within-season declines in peak intensity of competition were more pronounced for sub-elite players compared to elite players and for forwards compared to backs. Peak intensity within-season declines that were clear and greater than the smallest worthwhile difference tended to be of shorter durations (≤ 60 s) for the elite cohort, where the opposite was true for sub-elites (≥ 60 s). (**5**) The most intense 5-600 s passages of elite and sub-elite rugby union competition occurred near the middle of both match-halves on average. Between halves, peak intensities of matches occurred slightly later (~ 1-2 minutes) in the second half compared to the first for both competitions. (**6**) Elite and sub-elite rugby players who were on the field longer generally produced greater peak mean speed, metabolic power and PlayerLoad™ (ES > 0.2). Time on field influenced peak intensity to a greater extent in the second match-half compared to the first for both levels of competition.

Rugby union backs produced greater peak mean speed and metabolic power than forwards during both sub-elite and elite competitions across most durations from 5-600 seconds. Similarly in international rugby union match-play, outside backs, half-backs and loose forwards had small to moderate (ES range: 0.3-1.0) increases in relative distance and average acceleration than tight 5 (i.e. props, hooker, locks) forwards across all 1 to 10 minute moving average durations (Delaney et al., 2016d). Metabolic power was also likely greater for outside backs and half-backs when compared to tight 5 forwards (ES range: 0.9-1.0) (Delaney et al., 2016d). Peak relative distance and metabolic power differences between back and forward positional packs is logical given their respective roles they play for the team, rules of the game and their anthropometric profiles. Forwards are primarily tasked with securing possession of the ball and halting the progression of the opposition when not in possession of the ball (Lindsay et al., 2015). Given their increased involvement in collision-based events, forwards are generally heavier, taller and have an increased body fat percentage, absolute muscular strength and power compared to backs (Duthie et al., 2003). Given more force is required to move greater mass and that forwards are always in close proximity to opposition engaging in contact based events, total distance and distances covered at high speeds are reduced compared to backs who are lighter and have more space to engage with "free running" (Cunniffe et al., 2009; Quarrie et al., 2013). Training for the worst-case scenarios of competition should reflect positional role requirements by modulating player density (congestion of players in a given area) and rules to elicit desired player external loads and physiological adaptations.

The external load that rugby athletes experience is likely underestimated with the sole use of GPS measures, especially for forwards and as exercise duration increases. Peak relative distance and metabolic power were consistently greater for backs compared to forwards across 5-600 second epochs, however as exercise duration increased post 1 minute, accelerometer-derived PlayerLoad™ was greater for forwards than for backs. If player tracking durations continued beyond the 10 minute maximum sampling duration of the present study (e.g. half or whole match analysis), then the gradual accumulation of many movements that incur vertical or little horizontal displacement over time would result in further underestimation of external load via the sole use of GPS. If only GPS metrics were used to quantify external load, then these positional differences would not be detected and the coach would be led to believe that the forwards did not complete as much physical work as the backs, influencing subsequent recovery and training prescription. Further, the different type of external load forwards are exposed to would not be detected by the sole use of GPS metrics. External load has been recently proposed to be broadly segmented into physiological and biomechanical load-adaptation pathways (Vanrenterghem et al., 2017). During competition, rugby union forwards produce greater mean acceleration (Lacome et al., 2013), repeated high-intensity efforts (Jones et al., 2015), aggregated "body demands" (Owen et al., 2015), number of collisions (Reardon et al., 2017) and "static" bouts (i.e., scrums, rucks and mauls) (Roberts et al., 2008). Increased frequency, duration and often magnitude of collision-based movements alongside their increased body mass means forwards are exposed to greater biomechanical stress from other players and the ground when compared to backs, placing greater strain on the body's soft tissues. Any sport-specific or collision-based movements that involve vertical displacement (e.g. jumping, tackling) will not be measured by GPS and many rapid movements that incur little horizontal displacement are likely underestimated. This is largely a function of GPS only being able to quantify movement in two dimensions (x, y) and having one-tenth the sampling rate of accelerometers (100 Hz vs 10 Hz). Findings illustrate that practitioners should use accelerometers alongside GPS to more adequately quantify, monitor and prescribe intensity and external load during collision-based team sport training and competition.

Present findings suggest that professional rugby players preserve their ability to complete very high-intensity, short duration (≤ 30 s) movement across match-halves by reducing the amount of movement they perform at lower relative intensities of longer durations (≥ 60 s). This was evident as whilst longer duration efforts of lower relative intensity generally declined in the second match-half (up to 12%), efforts of shorter duration (≤ 30 s) and higher relative intensity exhibited trivial or small match-half reductions. The lack of decline in very high-intensity, short duration (≤ 30 s) peak movement between halves is similar to other professional rugby union time-motion analysis findings reporting "no change" in work-to-rest ratios (Lacome et al., 2013) and high-intensity running (Roberts et al., 2008) between match-halves. Moreover, high-intensity movements including: high-intensity running, sprinting, maximal accelerations, repeated high-intensity efforts and contacts did not considerably decline between professional rugby union match-halves (Jones et al., 2015). In contrast, players covered lower relative intensity cruising and striding distances as matches progressed, both within and between rugby union match-halves (Jones et al., 2015).

Reduced running volume and/or intensity during competition may be used to identify physiological impairment of a player, suggestive of transient fatigue (Waldron et al., 2013). It has been proposed that team sport athletes distribute their energy resources or 'pace' themselves in order to optimize running performance whilst avoiding the harmful failure of any physiological system (Waldron et al., 2014). The gradual decay of running intensity across progressive match periods is suggestive of players adopting a "slow-positive" pacing profile, common amongst many team sports (Waldron et al., 2014). Findings from the present study suggest that professional rugby players adopt a 'slow-positive' pacing strategy for lower relative intensity movements ≥ 60 s, whilst very high-intensity, shorter duration (≤ 30 s) profiles are typically 'flat' across matches, in accordance with others (Waldron et al., 2014). Altogether, rugby players may sacrifice the distances they cover at lower relative speeds to preserve their ability to complete very high-intensity, short duration efforts when the time arises during competition. Knowledge of duration-, position- and match-half-specific peak intensities of competition improves our understanding of athlete pacing strategies and may inform player substitution or rotation decisions.

Training relative to the average intensity of competition will leave professional rugby players substantially underprepared for the most intense periods of matches. As may be observed in Figure 5.1 and Figure 5.2, the whole-match average intensity of competition measured by mean speed, metabolic power and PlayerLoad™ in the present investigation was substantially lower than the peak 5-600 second intensities reported for both levels of competition, playing positions and match-halves. The average match intensity for pooled playing positions and match halves for elite (mean speed = 60.7 $m.min^{-1}$, metabolic power = 6.8 $W.kg^{-1}$, PlayerLoad™ = 0.5 au) and sub-elite (mean speed = 68 $m.min^{-1}$, metabolic power = 7.4 $W.kg^{-1}$, PlayerLoad™ = 0.51 au) rugby competition was substantially lower than the 5-600 second peak intensities reported for both playing positions and match-halves. For example, the 60 second most intense period of competition for elite backs averaged across both halves as quantified by the 3 measures was ~ 2.5-3 fold that of the match average intensities (mean speed = 165 $m.min^{-1}$, metabolic power = 20 $W.kg^{-1}$, PlayerLoad™ = 1.3 au). The same ~ 2.5-3 fold increase between the match average and 60 second peak intensity was true for the forwards (mean speed = 147 $m.min^{-1}$, metabolic power = 17 $W.kg^{-1}$, PlayerLoad™ = 1.4 au). Present findings are in concordance with others (Delaney et al., 2016d; Reardon et al., 2017), who have highlighted the stark discrepancies between whole-match average and peak intensities of professional rugby competition.

Fluctuations in running intensity are expected during rugby competition given its stochastic nature and whole-match averages are not sensitive enough to detect these subtle activity profile fluctuations (Delaney et al., 2016d; Furlan et al., 2015; Jones et al., 2015). Simply assessing the average intensity of competition hides the worst-case scenarios that players will be exposed to in matches. The intensity of training can be referenced against the peak periods of activity during competition to ensure the players are prepared for the rigours of match-play in a position- and duration-specific manner (Delaney et al., 2016d). This practice would theoretically increase the likelihood of players thriving and not just surviving during the peak periods of competition due to a reduced relative intensity for the adapted athlete. Coaches need to expose their athletes to very intense periods of training in a periodised manner using game-based methodologies such as small-sided games (Delaney et al., 2015) to elicit physiological adaptations (Rampinini et al., 2007b), reduce injury likelihood (Verrall et al., 2005) and improve athlete readiness to perform when confronted with worst-case scenarios during competition. The present findings have provided position specific intensities across GPS- and accelerometer-derived metrics for durations of 5 seconds to 10 minutes to help coaches prescribe training that is representative of the most intense periods of competition.

This study is the first to compare the most intense periods of elite vs. sub-elite rugby competition using GPS and accelerometer technology and rolling epoch analysis. The majority (74%) of 96 comparisons made between the most intense periods of elite versus sub-elite rugby competition yielded unclear or trivial differences, irrespective of duration, position, match-half or the measure used. Similarly, comparing the worst-case scenarios (defined as the longest period of ball in play) of European Rugby Championship (ERC) and Guinness Pro12 league competitions revealed that the vast majority of locomotor and collision measures were not significantly different between levels of rugby competition (Reardon et al., 2017). The ERC was considered the higher standard of rugby competition, as teams qualify for the ERC by finishing in a high ladder position in domestic leagues such as Pro12. The only statistically significant difference between the levels of competition was between the tight five forward positional group, where during ERC matches players covered greater high-speed running distance (8.9 $m.min^{-1}$) compared to their Pro12 counterparts (3.2 $m.min^{-1}$) (Reardon et al., 2017). These findings align to those of the present study, given the greater number of clear differences greater than the SWD observed between levels of competition for forwards vs. backs (20 vs. 5 respectively, cumulatively representing 26% of 96 comparisons). Sub-elite forwards produced greater peak mean speed and metabolic power than elite forwards during longer duration epochs (i.e. 300 and 600 s). However, elite forwards produced greater peak PlayerLoad™ than sub-elite forwards across shorter epoch durations (i.e. 5 to 120 s). Similar or greater running intensities (relative distance) reported in rugby union youth (Read et al., 2018b) compared to senior international players (Delaney et al., 2016d) may be due to improved defensive structures at international level, with youth academy defences allowing more space for players to run (Read et al., 2018b). This may explain why in the present study (where clear differences > SWD were reported) the sub-elite forwards produced greater peak mean speed and metabolic power yet lower PlayerLoad™ than elites, potentially attributable to less time spent in collision-based contests and more time in "open" spaces. Knowledge of the most physically intense periods of matches across different levels of competition or playing standards may inform the progression of duration- and position-specific conditioning as athletes move from one playing level to the next.

A novelty of this study was evaluating gradual changes in the most intense periods of both elite and sub-elite professional rugby across the course of their respective seasons.

The majority of within-season trends for peak mean speed and metabolic power were trivial or unclear across respective rugby seasons. However, for clear and substantial within-season trends, peak intensities of competition typically declined across respective seasons. Within-season declines in peak intensity of competition were typically more pronounced for sub-elite players compared to elite players and for forwards compared to backs. Contrary to our findings, high-speed, very-high speed running, sprint distance and sprint number during matches were all greater at the end of a professional AFL season compared to the beginning (Kempton et al., 2014). Increased high-speed activity during matches at the end of football seasons compared to the start may be due changes in team tactics, increased importance of matches leading into finals and improvements in player's physical capacity after repeated match exposures, leading to physiological adaptations (Kempton et al., 2014; Mohr et al., 2003; Rampinini et al., 2007a).

Given the nature of football movement is very complex and relates to a host of contextual factors (Paul et al., 2015), match-related factors (Murray et al., 2015) and individual player characteristics (Kempton et al., 2015a), it would be speculative to attempt to explain why peak intensities of competition tended to decline across elite and sub-elite rugby competitions in the present study. That being said, one possible explanation could be accumulated long-term fatigue reducing player's ability to complete high-intensity actions such as maximal accelerations and high-velocity running. Sub-elite rugby players potentially exhibited greater within-season declines in peak match intensities compared to elites because post-match fatigue is lower in player's with well-developed high-intensity running ability and lower body strength, despite these players having increased internal and external match loads (Johnston et al., 2015b). Although this explanation assumes the sub-elite rugby cohort in the present study had less developed high-intensity running ability and lower body strength, which is often the case (Quarrie et al., 1995; Smart et al., 2013), but was not directly measured in the present study.

A within-season decline in peak intensity was typically greater for sub-elite rugby forwards than backs across all external load measures. This was particularly evident during the peak 60 and 120 second periods of competition in the first match-half, where peak mean speed, metabolic power and PlayerLoad™ declined by 13 to 15% (ES range: 1.4-1.9). Reduced physical capacity of sub-elite footballers (Ingebrigtsen et al., 2012), paired with forwards engaging in more collision events that increase perception of effort (Johnston et al., 2011), muscle damage (Twist et al., 2012), neuromuscular fatigue (Johnston et al., 2014) and energy expenditure (Costello et al., 2018) may have led to accumulated long-term fatigue that reduced peak intensities achieved as the season progressed. Large within-season declines were observed for sub-elite forwards peak movement specifically for the 60 and 120 second epochs potentially due to these epoch durations approximating the average longest ball in play time duration of 152-161 seconds reported during professional rugby (Reardon et al., 2017).

The simple within-season linear trend model used in the present investigation may aid planning of individual and team training load. For example, a within-season trend of the peak intensities attained by players during competition rising or falling could inform on player physical readiness to play and inform the progression or regression of training volumes and intensities to balance fitness and fatigue in preparation for competition. Moreover, tracking within-season peak period of competition trends may aid monitoring of player’s speed and acceleratory capabilities and inform subsequent training prescription to improve these qualities. Future research should investigate non-linear peak intensity within-season trend models given evidence of non-linear dose-response relationships between training load and stress markers (Milanez et al., 2014), whilst including contextual factors (e.g. ball in vs. out of possession) and individual player characteristics (e.g. physical capacity) in such models.

The most intense passages of elite and sub-elite rugby union competition occurred near the middle of match-halves. Contrary to present findings, several measures of both low- and high-intensity movement and acceleration/deceleration progressively declined across successive 10 minute periods during professional rugby ($p < 0.05$), indicating the first 10 minutes of each match-half was of the highest intensity (Jones et al., 2015). Whilst the peak intensities of competition occurred near the middle of match-halves in the present study, the most intense passages of competition occurred at latter stages in the second match-half when compared to the first. Possibly, the most intense passages of matches occur later in the second match-half compared to the first due to increasing pressure to win the match with decreased time on the clock to do so. Identifying when the most intense periods of matches occur within each half may inform tactical decisions (e.g. player substitutions/rotations or formation changes). If consistent patterns of when these worst-case scenarios arose within competition emerged, then such data could inform warm up and half time re-warm up protocols if peak periods tended to be earlier in match-halves. Conversely, if the most intense periods consistently occur later in match-halves then this may suggest that players could benefit from training for these peak periods at the latter stages of training sessions under more duress or support the efficacy of their current training program.

Elite and sub-elite rugby players who were on the field longer generally produced greater peak mean speed, metabolic power and PlayerLoad™ (ES > 0.2). This finding makes intuitive sense, as players who are on field for longer have greater opportunity to express their physical prowess. Alternatively, those players on field for longer are typically older, more experienced and physically conditioned (Young et al., 2005). In contrast to the present findings, rugby substitutes (who have less time on field) exhibited increased running intensity than their starting and replaced counterparts (ES range: 0.2-0.5) (Lacome et al., 2016). However, substitute's short-term running intensity (i.e. first 10 minutes on field) was far superior to their long-term intensity. Whilst substitutes may provide an initial increase in physical intensity than starters and those that they replace (given they are physically "fresh"), several contextual and match-related factors govern the peak intensities they produce.

Time on field influenced the most intense passages of competition to a greater extent in the second compared to the first match-half across both levels of rugby competition. It is well established that more substitutions occur in the second half of rugby matches and that forwards are subbed more frequently than backs (Lacome et al., 2016; Quarrie et al., 2013). These common practices increased within-player standard deviations for time on field during the second match-half, especially for forwards (Table 5.1). Given influence of time on field was evaluated by standardising the change in peak intensity corresponding to two within-player standard deviations for each playing position and match-half across both levels of competition, the peak intensities were inevitably influenced more by time on field in the second half of matches.

Whilst the present investigation has provided several novel insights, it is not without limitation. Positional analyses were limited to positional packs (i.e. forwards and backs) rather than more specific playing positions (e.g., hooker, fly-half, full-back) to increase the precision of our estimates. Further, the case study nature of the present study may be considered a limitation and whilst two professional teams of two competitive levels with many repeated measures were included, league-wide investigations including opposition analyses would greatly improve our understanding of the peak intensity periods of rugby competition.

5.5 Practical Applications

Quantifying and characterising peak periods of both elite and sub-elite rugby competition using GPS- and accelerometer-derived measures may be practically used to:

- Design and prescribe duration- (5 seconds to 10 minutes) and position-specific (i.e. forwards, backs) training intensities (mean speed, metabolic power, PlayerLoad^{TM}) that replicate the most intense passages of elite and sub-elite rugby competition using game-based methods such as small-sided games to train tactical, technical and physical match elements simultaneously.
- Monitor and contextualise the intensity of training sessions.
- Inform player match readiness, influencing team selection.
- Inform player progressions during return to play.
- Inform player transitions between sub-elite and elite levels of competition.
- Inform match day substitutions or rotation decisions.
- Help determine the effect of rule modifications on player activity profiles.

- Inform the use of technologies: findings recommend the use of accelerometers alongside GPS to holistically quantify rugby external loads and detect duration- and position-specific differences during the most intense periods of competition.

5.6 Conclusions

Quantification and characterisation of the peak intensities of professional rugby using GPS and accelerometers has provided coaches with duration- and position-specific intensities to aid prescription and monitoring of match-specific training, whilst improving our understanding of factors that influence player peak intensities.

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CHAPTER 6: STUDY 4 - PROFESSIONAL RUGBY UNION ACTIVITY PROFILES POST PEAK PERIODS OF COMPETITION

6.1 Introduction

Several player tracking technologies and analysis techniques have been used to identify peak periods of player movement and quantify reductions in activity thereafter. Numerous studies have reported a decline in player distance covered and high-intensity activity within and between match-halves, possibly indicative of transient or accumulated fatigue (Jones et al., 2015; Mohr et al., 2003). For instance, professional rugby union athletes performed the highest relative distance in the first 10 minutes of each match-half, declining thereafter (Jones et al., 2015). Distance travelled during the first 5 minutes of each rugby league match-half was significantly higher than the 5 minute periods later in the halves ($p < 0.001$) (Kempton et al., 2013). Large reductions in total distance covered comparing the peak 5-minute period to the period immediately subsequent were also observed ($p < 0.001$) (Kempton et al., 2013). Greater high speed running distance ($\geq$ 14.4 km.h^{-1}) was covered in the first versus the final 5 minutes of soccer matches and in the peak 5 minutes of activity compared to the subsequent and mean 5 minute periods ($p < 0.05$) (Carling et al., 2011). In concert, during professional soccer competition, high-intensity running distance ($\geq$ 15 km.h^{-1}) was 35-45% lower in the last 15 minutes of matches compared to the first, independent of competitive standard and playing position (Mohr et al., 2003). Post the peak pre-defined 5 minutes of high-intensity running for the entire match, distance covered at high-intensity declined by 12% in the subsequent 5 minutes compared to the match average (Mohr et al., 2003). However, the most intense periods of player movement during a match do not fall completely within pre-defined periods of time, and therefore likely underestimate peak periods and overestimate subsequent periods of activity (Cunningham et al., 2018; Ferraday et al., 2020; Varley et al., 2012a).

During professional soccer competition, peak high-velocity ($\geq$ 4.17 m.s^{-1}) running distance was underestimated by up to 25% using pre-defined time period analysis, with the subsequent period distances overestimated by up to 31% when compared to rolling time period analysis. When the distance decline in high-velocity running between the peak and following period were examined, there was up to a 52% greater reduction in running performance using rolling vs. pre-defined periods (Varley et al., 2012a). Therefore, it was recommended that researchers and practitioners use rolling or moving average time period analyses when trying to accurately identify and quantify the peak periods of football competition and movement thereafter (Varley et al., 2012a).

Accurately quantifying the inevitable intensity decline directly after peak periods of matches may improve our understanding of professional rugby players pacing strategies. Such data may inform match-specific high-intensity interval training (HIIT) prescription, programming for both high-intensity periods and for "active recovery" periods. No study to date has used a large range of rolling epochs to examine movement intensity post peak periods using Global Positioning Systems (GPS) and accelerometry. Player movement after the most intense passages of competition is likely dependent on the duration of the peak period analysed, competition level and playing position. Little evidence exists detailing the time-course of player activity profiles following peak periods of competition comparing these factors. Therefore, the aim of this study was to quantify rugby union athlete activity profiles post the most intense 5-600 seconds of professional competition.

6.2 Methods

Many methods pertaining to the participants, equipment and data collection, measures of peak movement and data filtering and processesing have been established and described in detail (Chapter 4, methods section). Consequently, in this chapter these methods will be described in brief, with more detail of the novel statistical analyses investigating rugby player activity profiles post the peak periods of professional competition.

6.2.1 Methodology – In brief

Movement data were collected from 30 elite and 30 sub-elite professional rugby union athletes across respective seasons. Player movement data were collected via commercially available OptimEye™ S5 GPS and GLONASS-enabled receivers with an embedded tri-axial piezoelectric accelerometer (firmware version 7.22, Catapult Sports, Melbourne, Australia). Accelerometer-derived PlayerLoad™ and Global Positioning Systems (GPS) derived measures of mean speed ($m.min^{-1}$) and metabolic power ($W.kg^{-1}$) were analysed using a rolling average to identify the maximum mean (peak) values for 5, 10, 20, 30, 60, 120, 300 and 600 second durations. Rolling average time-motion methodology (Delaney et al., 2015; Varley et al., 2012a) and detailed descriptions of the three external load measures (Aughey, 2011; Boyd et al., 2011; Osgnach et al., 2010) have been previously established (Chapter 3 & 4).

Player activity profiles immediately post their maximum mean (peak) 5 to 600 s were identified using five epoch duration-matched intervals. Using the 60 s (1 minute) epoch as an example, the peak 1 minute intensity during competition was identified for each measure (i.e. PlayerLoad^{TM}, mean speed and metabolic power) using a rolling average and then subsequent activity was measured across five duration-matched 1 minute epochs (i.e. 0 to 1, 1 to 2, 2 to 3, 3 to 4 and 4 to 5 minutes). Five duration-matched intervals were chosen to enable fair comparison between intensities during the peak and subsequent periods, with five intervals chosen arbitrarily to reveal the time-course of intensity fluctuations post the most intense passages of play.

6.2.1 Statistical Analyses

Each of the three measures of maximum mean movement were analysed with the general linear mixed modelling procedure (Proc Mixed) in SAS. The measures were log-transformed prior to analysis to reduce non-uniformity of error (Hopkins et al., 2009). The fixed effects in the model were player position (backs, forwards) interacted with match-half (1st, 2nd), interacted with time on the field to adjust for this variable. The random effects in the model were player identity and match identity.

Peak 5 to 600 second values for the three movement measures alongside values for each of the five duration-matched subsequent intervals were calculated as means ± SD (Figures 6.1 to Figure 6.6). The effect of peak intensity attained during any given duration on subsequent movement during the five duration-matched intervals post peak was also assessed via percent decline from peak (Table 6.2). The match-half mean intensity for each measure is presented (dashed line, Figures 6.1 to 6.6) to provide an easy visual gauge of the influence of peak intensity periods on player activity profiles post.

The smallest worthwhile difference (SWD) or change in means is 0.2 standard deviations; thresholds for moderate, large and very large differences are 0.6, 1.2 and 2.0, respectively (Hopkins et al., 2009). Uncertainty in effects was expressed as 90% compatibility limits or intervals and as probabilities that the true effect was substantially positive and negative. These probabilities were used to make a qualitative probabilistic non-clinical magnitude-based decisions (MBD) about the true effect (Hopkins et al., 2009): if the probabilities of the effect being substantially positive and negative were both > 5%, the effect was reported as unclear. The scale for interpreting the probabilities was as follows: 25-75%, possible; 75-95%, likely; 95-99.5%, very likely; > 99.5%, most likely. "Substantial" differences were considered as those that met the following criteria: ES ≥ 0.2 (SWD) and ≥ 75% likely.

Table 6.1 Total number of player movement files analysed across five duration-matched intervals (Int 1-5) post the peak periods of elite and sub-elite rugby

Elite (Super 15 Rugby) mean speed files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	416	415	415	413	394
10	416	417	407	393	382
20	418	404	403	396	398
30	411	404	397	388	390
60	403	386	371	367	368
120	377	357	345	327	303
300	358	271	244	208	166
600	274	200	94	1	0

Sub-elite (NRC) mean speed files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	268	266	264	264	265
10	263	260	262	262	260
20	262	265	261	258	258
30	264	260	259	257	252
60	255	246	248	240	230
120	254	240	225	205	182
300	221	172	131	97	70
600	130	58	29	0	0

Elite (Super 15 Rugby) PlayerLoad™ files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	420	419	420	416	414
10	418	415	409	406	407
20	415	407	406	401	400
30	410	405	406	405	400
60	404	389	381	379	366
120	378	350	335	320	302
300	346	276	247	215	175
600	285	203	99	4	0

Sub-elite (NRC) PlayerLoad™ files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	269	264	264	265	265
10	261	258	260	257	257
20	258	254	254	253	250
30	261	256	253	248	246
60	256	242	235	224	219
120	250	236	224	208	182
300	212	178	140	108	78
600	143	76	42	0	0

Elite (Super 15 Rugby) metabolic power files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	405	413	409	405	400
10	416	412	409	398	376
20	409	395	396	388	382
30	399	395	388	384	376
60	402	376	366	349	346
120	372	335	322	318	285
300	319	235	205	175	150
600	218	130	74	2	0

Sub-elite (NRC) metabolic power files					
Epoch Duration (s)	Int 1	Int 2	Int 3	Int 4	Int 5
5	262	265	266	263	261
10	264	261	263	263	261
20	260	261	255	251	250
30	266	259	254	251	248
60	258	241	240	228	219
120	245	227	215	192	170
300	206	151	115	92	66
600	106	46	25	0	0

6.3 Results

6.3.1 Activity profile declines post peak periods of competition

Exercise intensity measured by mean speed, metabolic power and PlayerLoad^{TM} declined sharply (~ 29 to 86%) post the most intense 5 to 600 seconds of competition (Table 6.2 and Figures 6.1 to 6.6). Shorter duration, higher-intensity peak periods caused larger declines in movement intensity during subsequent periods (Table 6.2 and Figures 6.1 to 6.6). For example, player exercise intensities declined by ~ 78 to 86% post the peak 5 to 30 seconds of elite and sub-elite rugby competition. In contrast, player exercise intensities declined by ~ 30% post the peak 600 seconds across both levels of rugby (Table 6.2). Using Figure 6.1, panel A as an example, the 5 second peak mean speed for backs in the first half was 423 $m.min^{-1}$ (7.1 $m.s^{-1}$ or 25 $km.h^{-1}$), with intensity declining 79% to an average of 88 $m.min^{-1}$ (1.5 $m.s^{-1}$ or 5.3 $km.h^{-1}$) in the following 25 seconds (five duration-matched intervals post). On the other end of the duration spectrum, the 600 second peak mean speed for backs in the first half was 82 $m.min^{-1}$ with intensity declining 29% to 58 $m.min^{-1}$ during the five intervals post.

In general, there were greater exercise intensity declines post the peak periods of elite competition as measured by PlayerLoad^{TM} (69%) and metabolic power (69%) when compared to mean speed (66%) when averaged across 5 to 600 second epochs, both positions and match-halves (mean difference ~ 3%, Table 6.2). Similarly, in sub-elite rugby greater exercise intensity declines (~ 5%) were measured by PlayerLoad^{TM} (66%) and metabolic power (66%) when compared to mean speed (61%). The largest intensity decline disparity between the three measures was post the peak 20 s of sub-elite competition (mean speed declined 63% vs. metabolic power and PlayerLoad^{TM} declining 84 and 85% respectively, Table 6.2).

The half-mean exercise intensity (dashed lines, Figures 6.1 to 6.6) was greater than exercise intensities post the peak 5 to 600 s intensities of competition on 742 of 911 interval 1 to 5 occasions (81%).

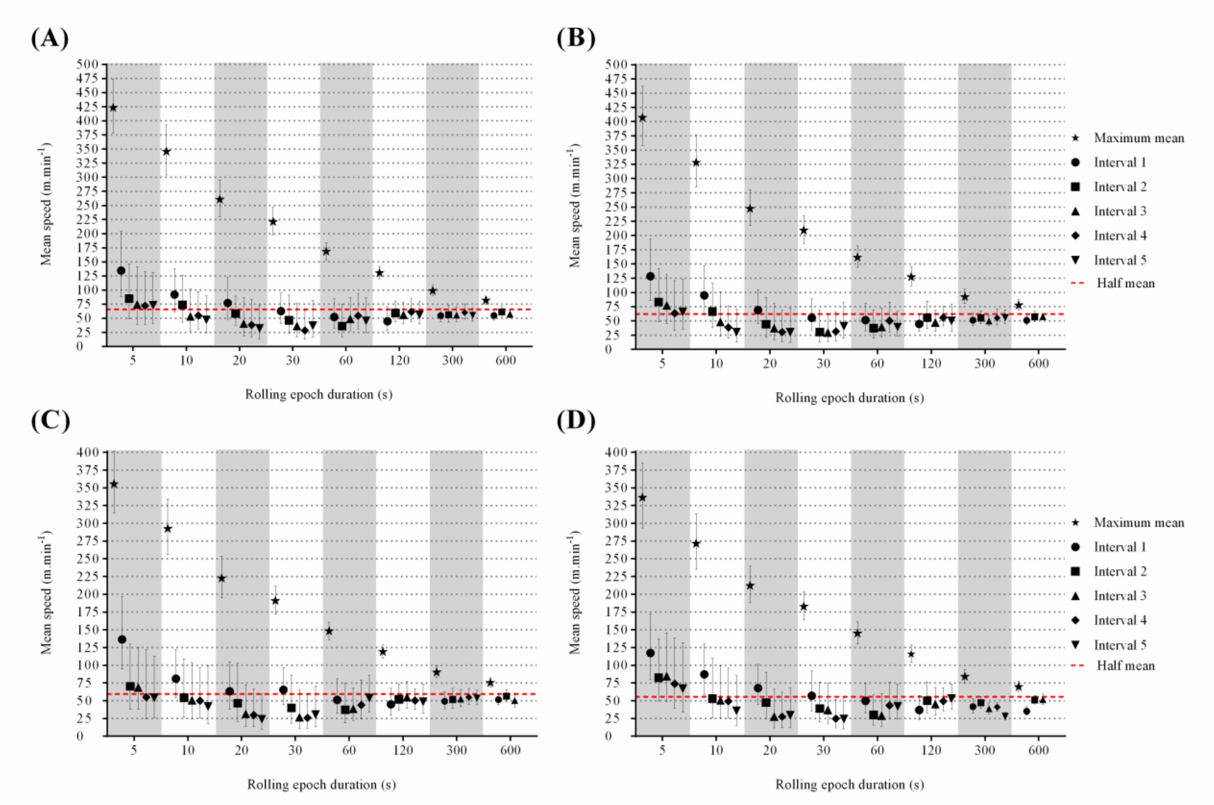


Figure 6.1 Super 15 Rugby duration specific (5-600 s) maximum mean speed (m.min^{-1}) and mean speed post (duration-matched intervals 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation.

Table 6.2 Exercise intensity declines post 5 to 600 second peak intensities of elite and sub-elite rugby competition.

Exercise intensity declines post peak intensities of rugby competition (%)								
Epoch duration (s)	**5**	**10**	**20**	**30**	**60**	**120**	**300**	**600**
Mean speed								
Elite backs	79	82	82	81	71	59	42	29
Elite forwards	78	81	82	80	70	58	42	30
Sub-elite backs	80	82	63	76	66	53	39	24
Sub-elite forwards	77	82	78	75	65	53	37	26
Epoch duration (s)	**5**	**10**	**20**	**30**	**60**	**120**	**300**	**600**
Metabolic power								
Elite backs	85	88	86	84	76	62	43	28
Elite forwards	84	84	84	82	73	62	42	32
Sub-elite backs	86	88	85	82	73	59	41	34
Sub-elite forwards	84	84	80	74	64	52	36	25
Epoch duration (s)	**5**	**10**	**20**	**30**	**60**	**120**	**300**	**600**
PlayerLoad™								
Elite backs	86	86	86	85	78	65	47	31
Elite forwards	86	85	85	80	71	61	41	29
Sub-elite backs	88	88	84	81	69	57	41	42
Sub-elite forwards	83	83	76	74	64	53	38	25
Epoch duration (s)	**5**	**10**	**20**	**30**	**60**	**120**	**300**	**600**
Measures & positions averaged								
Elite rugby	83	84	84	82	74	61	46	31
Sub-elite rugby	83	85	79	78	68	55	39	29
Difference (%)	0.0	-0.9	5	4	6	6	7	2

Each measure was averaged across peak period duration-matched intervals 1-5 post and across both match-halves.

6.3.2 Match-half activity profile differences post peak periods of competition

Of the 229 elite match-half activity comparisons during intervals 1 to 5 post peak 5 to 600 second intensities, only 37 or 16.2% were “substantial” (i.e. ES $\geq$ 0.2 and $\geq$ 75% likely). All substantial match-half effects were of small to moderate magnitude (ES range: 0.2 to 1.1, 75 to 99.8% likely). Of the 37 substantial differences, 32 or 87% revealed reduced exercise intensity post the peak intensities of competition in the second compared to the first match-half.

Of the 226 sub-elite match-half activity comparisons during intervals 1 to 5 post peak intensities, 79 or 35% were substantial. Each measure of mean speed, metabolic power and PlayerLoad^{TM} contributed 25, 27 and 27 substantial differences respectively of the 79 total, with no evident epoch duration trends. Whilst the majority (65%) of 226 match-half differences were either trivial or unclear, 77/79 interval 1 to 5 comparisons revealed substantial intensity declines during the second compared to first match-halves. Of the 79 substantial sub-elite match-half differences, 75% revealed forwards had decreased exercise intensity post the peak 5 to 600 seconds of competition when compared to backs (ES range: 0.3 to 1.1, 77 to 99% likely).

6.3.3 Positional activity profile differences post peak periods of competition

Exercise intensity declines post the peak 5 to 600 seconds of rugby were mostly similar between positional groups across both levels of competition. Of the 229 elite and 226 sub-elite interval 1 to 5 post peak comparisons, 76 and 79% respectively displayed no substantial differences between positions. Where substantial differences were evident between forwards and backs (elite: 55/229, sub-elite: 48/226), the majority (elite: 23, sub-elite: 32) were detected by PlayerLoad^{TM}. Where substantial active recovery profile differences existed between positions, mean speed and metabolic power were greater for backs than forwards for 32/32 elite and 15/16 sub-elite intervals (ES: 0.3 to 1.7, ≥ 75% likely). In contrast, PlayerLoad^{TM} was greater for forwards vs. backs for 22/23 elite and 27/32 sub-elite intervals (ES: 0.3 to 1.5, ≥ 75% likely).

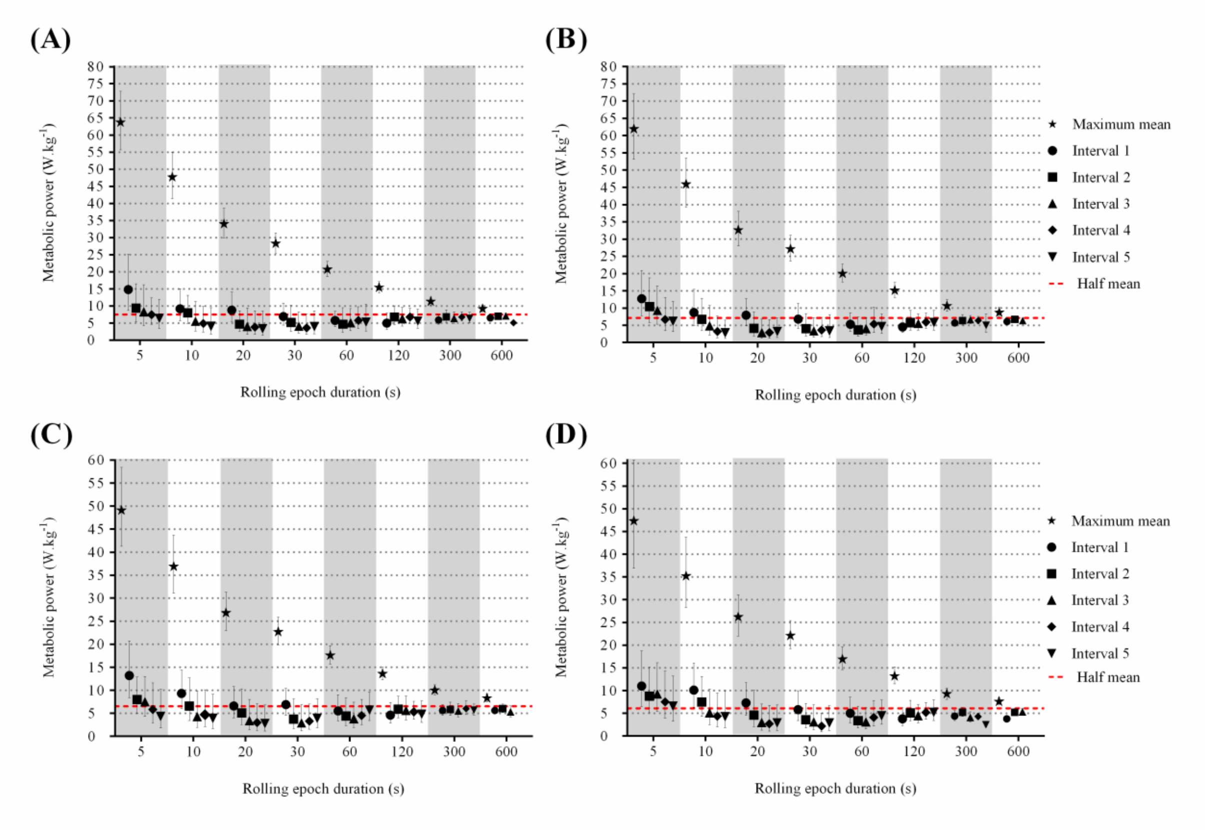


Figure 6.2 Super 15 Rugby duration specific (5-600 s) maximum metabolic power (W.kg^{-1}) and metabolic power post (duration-matched intervals 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation

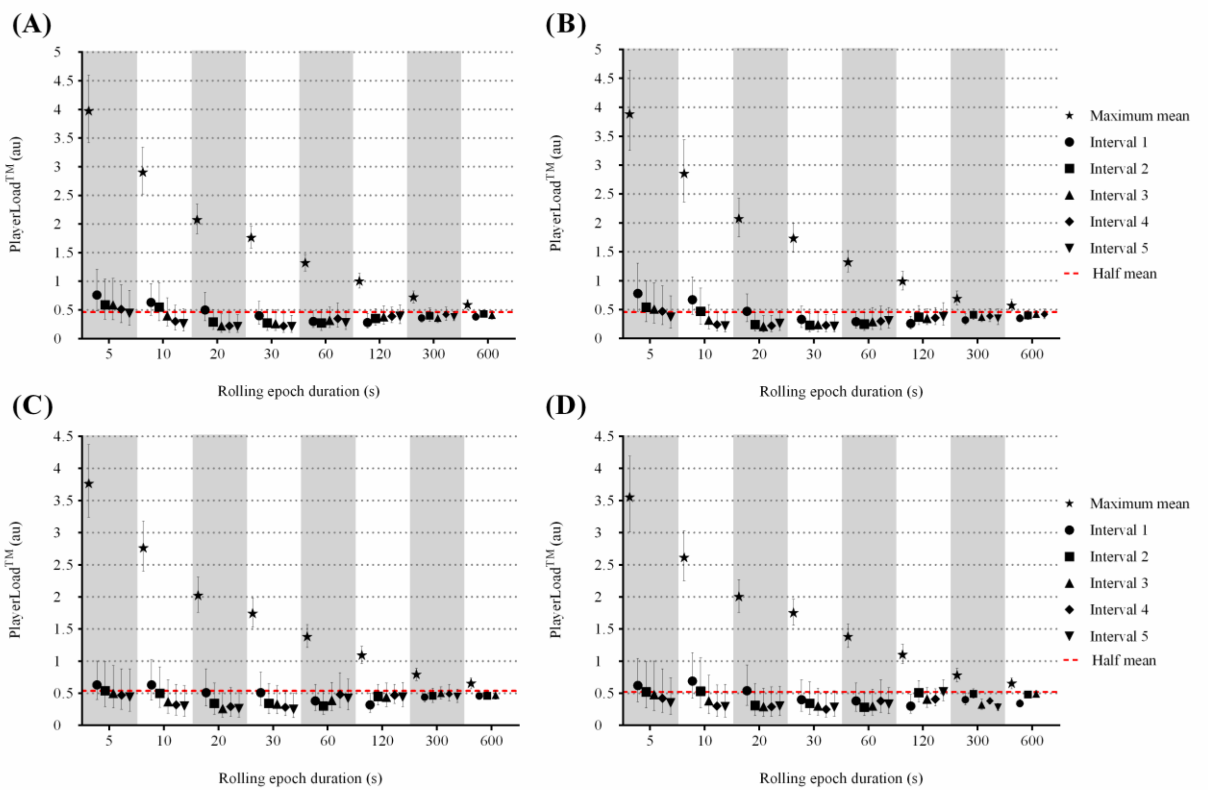


Figure 6.3 Figure 3: Super 15 Rugby duration specific (5-600 s) maximum mean PlayerLoad^{TM} (au) and PlayerLoad^{TM} post (duration-matched intervals 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation

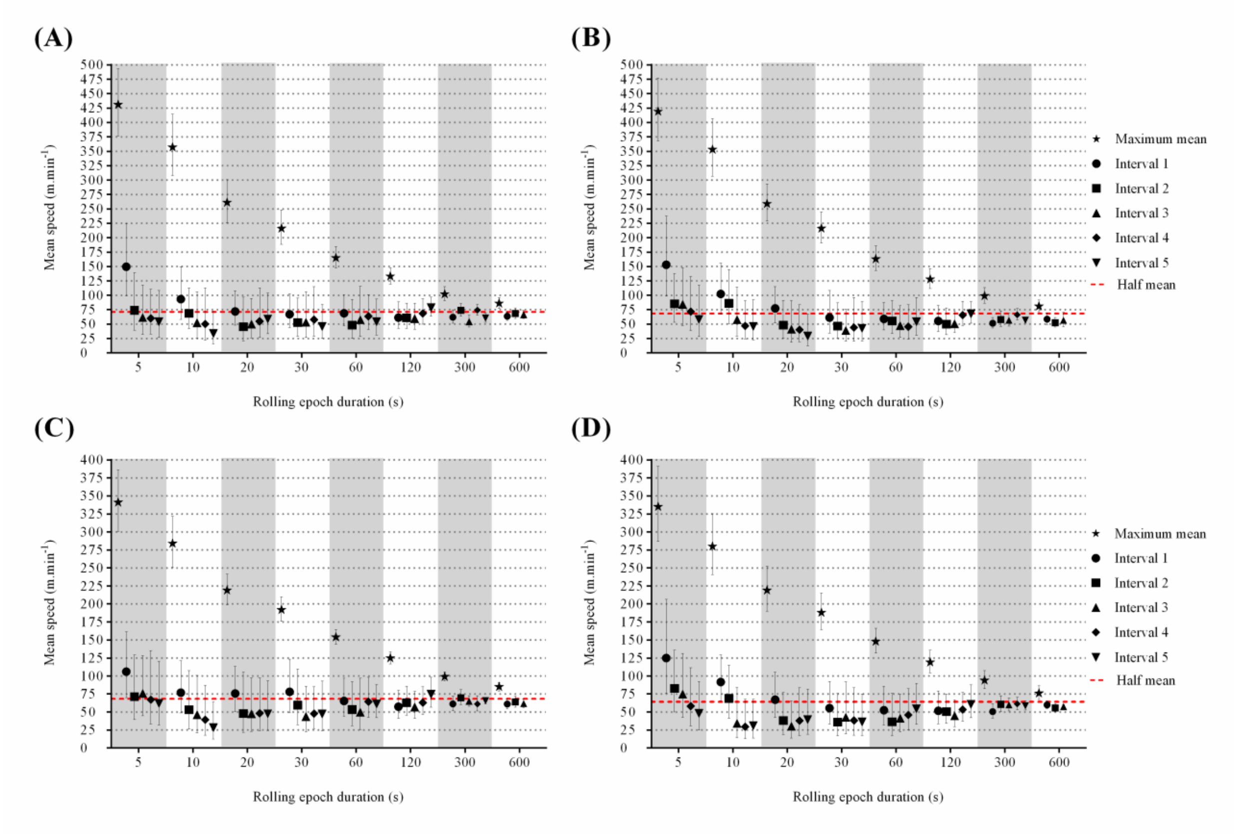


Figure 6.4 National Rugby Championship duration specific (5-600 s) maximum mean speed (m.min^{-1}) and mean speed post (duration matched intervals of 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation.

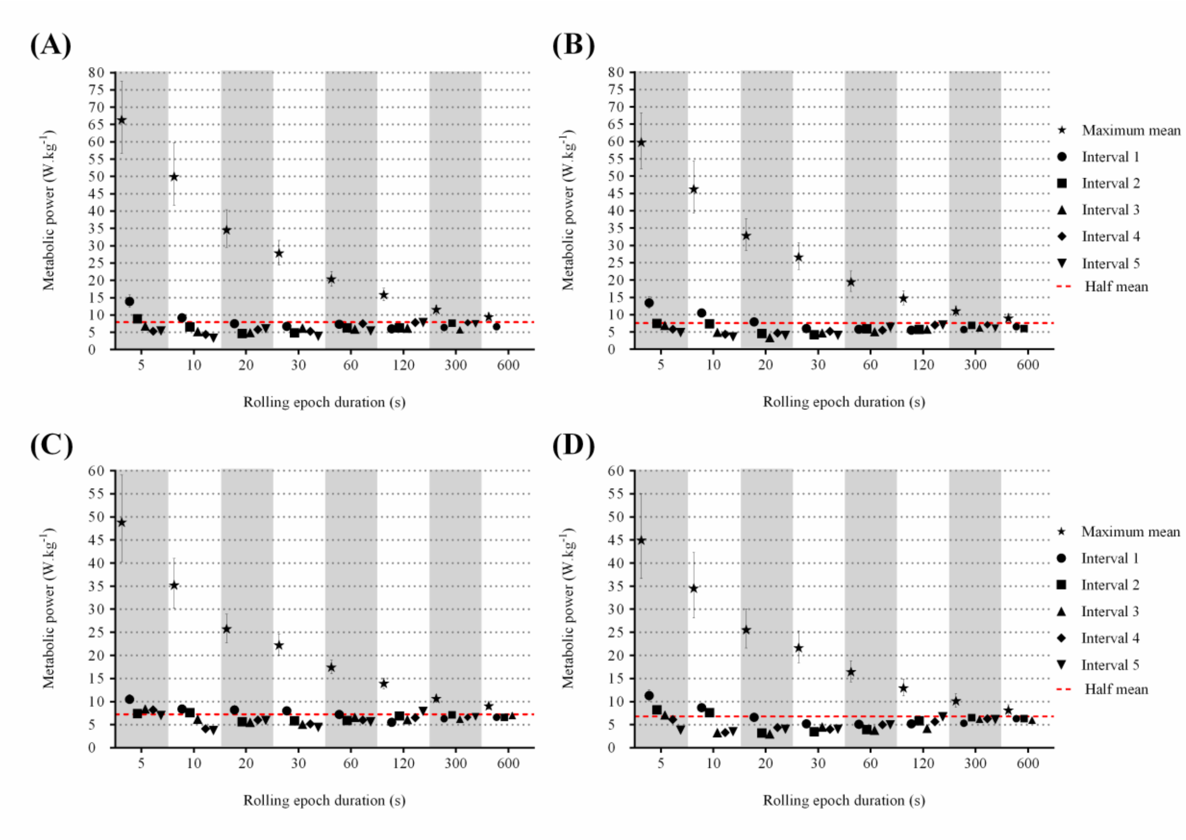


Figure 6.5 National Rugby Championship duration specific (5-600 s) maximum metabolic power (W.kg^{-1}) and metabolic power post (duration-matched intervals 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation.

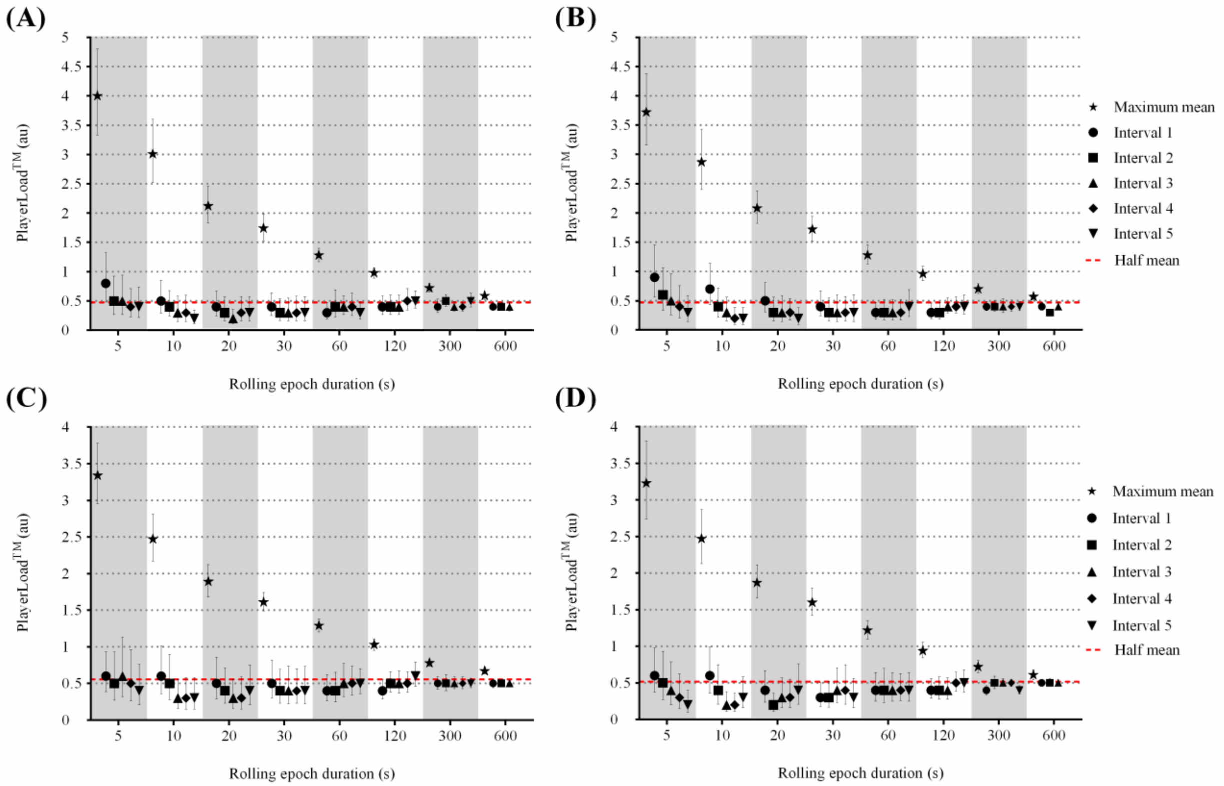


Figure 6.6 National Rugby Championship duration specific (5-600 s) PlayerLoad™ (au) and PlayerLoad™ post (duration-matched intervals 1-5). Panels by playing position and match-half. (A); backs 1st match-half, (B); backs 2nd match-half, (C); forwards 1st match-half, (D); forwards 2nd match-half. Data presented are means ± standard deviation.

6.4 Discussion

The aim of the present investigation was to quantify rugby union activity profiles post the most intense periods of professional competition. This study was the first to sequentially track the time-course of exercise intensity decline post the most intense periods of team sport competition using GPS and accelerometry. Mean speed, metabolic power and PlayerLoad™ declined sharply (~ 29 to 86%) post the most intense 5 to 600 seconds of professional rugby competition, with the magnitude of decline principally dependent on the peak intensity attained during any given period.

Typically, exercise intensity declines post the peak 5 to 600 seconds of professional rugby competition were similar between match-halves, positional groups and levels of competition. However, where substantial (i.e. ES $\geq$ 0.2 and $\geq$ 75% likely) differences arose, exercise intensity post peak periods of competition declined to a greater extent in second match-halves, backs produced greater mean speed and metabolic power, whereas forwards produced more PlayerLoad™.

Consistently PlayerLoad™ and metabolic power quantified a larger exercise intensity decline (~ 3 to 5%) post peak periods than mean speed. Accelerometer-derived PlayerLoad™ detected the majority of substantial positional differences post peak periods, indicating improved sensitivity compared to GPS-derived measures in doing so. Post the most intense periods of rugby competition, exercise intensity declined below the average match-half intensity (i.e. mean speed, metabolic power and PlayerLoad™) 81% of the time and rarely returned to or exceeded it. Exercise intensity declines post peak periods of rugby competition were typically greater during elite vs.

sub-elite matches by ~ 4%. The following sections will describe present findings in light of others.

Findings suggest elite and sub-elite rugby players reduce their exercise intensity dramatically (by up to 86%), with exercise intensity below the average ~ 40 minute match-half mean speed, metabolic power and PlayerLoad^{TM} 81% of the time (Figures 6.1 to 6.6). Post the most intense periods of professional rugby matches, exercise intensity rarely (19%) returns to the match-half average intensity. Similarly, several professional football investigations have observed large reductions in exercise intensity post the peak periods of competition (Table 6.3) (Black et al., 2016; Furlan et al., 2015; Kempton et al., 2013; Kempton et al., 2015b; Varley et al., 2012a). During elite rugby sevens competition, running intensity was reduced to a very large extent (46-64%) following the most intense 2 minute period of the match (relative distance ES: 2.9, metabolic power ES: 4.1, both $p < 0.001$) identified using rolling average epoch analyses (Table 6.3) (Varley et al., 2012a). Moreover, during professional rugby league the most physically intense 5 minutes of competition was significantly greater than both the subsequent (ES range: 1.7-3.5) and mean (ES range: 2.0-4.3) 5 minute periods for total distance, high-speed distance, high-power distance and metabolic power ($p < 0.001$) (Kempton et al., 2015b).

Accurate identification of the peak intensities of competition using rolling epoch analysis and quantifying subsequent exercise intensity declines improves our limited understanding of team sport athlete pacing strategies and fatigue, which may inform match-day substitution or rotation decisions, player positional changes and team formations. For instance, live player movement data may be collected via GPS receivers and relayed to a receiver antenna connected to a computer, with proprietary software allowing for real-time player movement tracking. If historical data have been collected on the previous peak intensities of competition for a cohort of interest (assuming rolling epoch averages could be programmed into software), it would be possible in real-time to identify similarly intense periods (via pre-defined alerts set within the software). Alternatively, practitioners could use the peak, post peak and average intensities of competition quantified in the present investigation and others (see Table 6.3) as reference values for the football code of interest to set alerts within player tracking software. Consequently, it is possible to identify very intense periods of competition in real-time during matches and quantify inevitable declines in exercise intensity thereafter. Such data may be relayed from the person watching and interpreting the live data stream (e.g. sport scientist) to a coach, ideally providing them with context around the values such as the current match average exercise intensity and/or normative historical values for the team, position or player of interest. Preferably, such activity profile data would be used in conjunction with performance analyst technical key performance indicators to help inform the coach's expert opinions on tactical decisions, such as player substitutions and team formations.

Table 6.3 Comparison of peak, post peak and average intensities of professional football competition.

Football Code	Epoch	Half	Peak Intensity	Post Peak Intensity	Decline (%)	Average Intensity
Soccer (Varley et al., 2012a)	5 mins	1st 2nd	177 $m.min^{-1}$ 166 $m.min^{-1}$	64 $m.min^{-1}$ 52 $m.min^{-1}$	↓64% ↓69%	Not reported
Rugby League (Kempton et al., 2015b)	5 mins	Both	108 $m.min^{-1}$ 11 $W.kg^{-1}$	81 $m.min^{-1}$ 8 $W.kg^{-1}$	↓25% ↓26%	86 $m.min^{-1}$ 9 $W.kg^{-1}$
Rugby Sevens (Furlan et al., 2015)	2 mins	Both	~ 130 $m.min^{-1}$ ~ 13 $W.kg^{-1}$	~ 70 $m.min^{-1}$ ~ 5 $W.kg^{-1}$	↓46% ↓64%	~ 95 $m.min^{-1}$ ~ 10 $W.kg^{-1}$
Rugby Union (present study, Super Rugby data)	2 mins	1st 2nd	125 $m.min^{-1}$ 121 $m.min^{-1}$	45 $m.min^{-1}$ 41 $m.min^{-1}$	↓64% ↓66%	62 $m.min^{-1}$ 59 $m.min^{-1}$
	2 mins	1st 2nd	15 $W.kg^{-1}$ 14 $W.kg^{-1}$	5 $W.kg^{-1}$ 4 $W.kg^{-1}$	↓67% ↓71%	7 $W.kg^{-1}$ 7 $W.kg^{-1}$
	5 mins	1st 2nd	94 $m.min^{-1}$ 88 $m.min^{-1}$	52 $m.min^{-1}$ 47 $m.min^{-1}$	↓45% ↓47%	
	5 mins	1st 2nd	11 $W.kg^{-1}$ 10 $W.kg^{-1}$	5 $W.kg^{-1}$ 5 $W.kg^{-1}$	↓54% ↓50%	

Mean speed ($m.min^{-1}$), Metabolic power ($W.kg^{-1}$)
Percent decline comparisons made using rolling 2- and 5-minute averages with comparative 2- and 5-minute epochs post. Data averaged across reported positional groups.

Temporal exercise intensity reductions have been used as evidence of match-related fatigue during football competition (Kempton et al., 2013; Mohr et al., 2003). Multiple central and peripheral physiological mechanisms underpin these reductions in physical performance, such as reduced motor drive, glycogen depletion and accumulation of metabolites to name a few, ultimately impeding excitation-contraction coupling (Ament et al., 2009). Alternatively, a decline in physical output may be due to players adopting pacing strategies in an attempt to distribute their energy resources throughout a match

(Waldron et al., 2014). Whilst numerous investigations have examined pacing during team sport competition, it is very difficult to establish its existence as fluctuations in exercise intensity may also be due to match-related fatigue and other contextual factors (Aughey, 2010; Kempton et al., 2015b). These contextual factors have been broadly classified into: situational factors, match-related factors and individual player characteristics (Kempton et al., 2015a). Situational factors relate to things such as opposition strength (Gabbett, 2013) and between match recovery time (Murray et al., 2014). Match-related factors include but are not limited to: possession status (Gronow et al., 2014), match scoreline (Sullivan et al., 2014), playing formation (Bradley et al., 2011), field position and phase of play (Gabbett et al., 2014) and team success (Hulin et al., 2015b). An individual's exercise intensity during match-play is also underpinned by their physiological qualities (Duthie et al., 2017). The sharp decline in physical activity following the peak periods of professional rugby competition in this study are suggestive of player's pacing their efforts to minimize physiological stress and transient fatigue as they attempt to recover from intense exercise bouts (Furlan et al., 2015). However, a myriad of contextual factors likely contribute to rugby players reducing their exercise intensity post these peak periods of competition and warrant future investigation.

The physical activity profile of players is only of importance if physical prowess improves a player's ability to execute their technical and tactical roles effectively to help their team win. The effect of intense periods of competition on physical and technical performance of elite AFL athletes was investigated and compared between more and less experienced players (Black et al., 2016). Peak physical and technical skill performance were analysed using a 3 minute rolling average approach (Varley et al., 2012a), as 6 minutes was the minimum amount of time between player rotations at the football club. Following the most intense 3 minute period of competition, the experienced players ran greater distances at high-speeds in match quarters two (ES ± 90% CI = 0.4 ± 0.3) and three (0.4 ± 0.3) than less experienced players. Relative to their less experienced counterparts, experienced players performed more skill involvements during the second (0.4 ± 0.3) and fourth quarter peak 3 minute bouts of exercise intensity (0.4 ± 0.3). Experienced players also performed a greater number of skilled involvements directly after the most intense 3 minutes of match quarters one (0.5 ± 0.3) and three (0.3 ± 0.2), when compared to less experienced players. Less experienced elite AFL players displayed greater reductions in both physical and technical performance following the most intense passages of competition. Findings suggested that it may be pertinent to regularly, progressively and periodically expose less experienced players to the worst-case scenarios of competition so that they are better able to maintain high physical intensities and gain possession of the football during and following these very high-intensity periods. Further, authors proposed that coaches consider rotating less experienced players on and off the field more frequently in an effort to prevent declines in exercise intensity following the most intense passages of play (Black et al., 2016).

In contrast to the findings in AFL, this study found that when compared to the more experienced elite rugby cohort, the sub-elite players (generally less experienced) typically produced slightly greater (~ 4%, Table 6.3) exercise intensities post the peak periods of competition. One potential reason for this is that it is common in higher levels of rugby competition to observe greater frequency and magnitude of collision-based events, potentially leading to reductions in player movement thereafter due to structural muscle damage (Takarada, 2003). Following the most intense 5 minute period of professional rugby league competition there were significant reductions in distance covered, quantity and quality of skilled involvements and contextual factors (ball in play time) (all $p < 0.001$) (Kempton et al., 2013). Further research is required to elucidate the influence of competition level and several contextual factors on physical, technical and tactical performance during and post the most intense periods of rugby competition.

Typically, exercise intensity declines post the peak 5-600 seconds of professional rugby competition were similar between match-halves, positional groups and levels of competition. However where substantial differences arose, exercise intensity post peak periods of competition declined to a greater extent in second match-halves, backs produced greater mean speed and metabolic power, whereas forwards produced more PlayerLoad^{TM}. Moreover, sub-elite rugby players typically displayed higher exercise intensities post peak periods of matches compared to their elite counterparts. The following sections will briefly discuss both the lack of match-half, positional and level of competition differences whilst mentioning some substantial differences relative to previous investigations.

Post peak match-half findings of this study are in contrast with the majority of previous investigations revealing that rugby union athletes generally exhibit a 'slow-positive' pacing profile for lower-intensity movements and a 'flat' pacing profile for higher-intensity movements across matches.(Waldron et al., 2014) A 'slow-positive' pacing profile indicates that players reduce low intensity movements as match's progress and 'flat' pacing profiles indicate that exercise intensity is maintained across match periods (Waldron et al., 2014). The severe exercise intensity reductions post the peak periods of rugby competition in the present study were generally similar across match-halves, indicating very low intensity movement typically remains 'flat' across professional rugby match-halves. However, during sub-elite rugby competition, 35% of all post peak period comparisons revealed exercise intensity substantially declined in second match-halves and that these declines were more frequent and severe for forwards than backs (ES range: 0.3-1.1). This finding suggests that sub-elite rugby players may preserve their energy by completing less low-intensity activity after very intense periods of competition in the second half so that they may recover to a greater extent in order to complete higher-intensity tasks when called upon to do so. Reduced low-intensity activity post peak periods of rugby competition may impede player's ability to maintain defensive position or run supporting lines in attack (Roberts et al., 2008). This investigation provides some support for current conventional practice (Waldron et al., 2014), making more substitutions during second match-halves and substituting forwards more often than backs.

Sharp reductions in exercise intensity after the most intense periods of elite and sub-elite rugby competition are similar between positional groups (backs and forwards). In contrast, professional AFL midfielders consistently displayed greater total distance, low speed activity, moderate speed running and high speed running distance than key position players during and post the peak 3 minutes of competition (Black et al., 2016). Unfortunately, there is a dearth of literature investigating positional movement differences after the most intense periods of football competition, with studies tending to group playing positions (e.g. see Table 6.3) (Furlan et al., 2015; Kempton et al., 2015b; Varley et al., 2012a). Given rugby forwards are typically heavier, taller and have a greater percentage of body fat, backs have greater relative aerobic and anaerobic power, forwards spend greater time in contact whilst backs in free running, and forwards complete greater total work with lower work: rest ratios than backs (Duthie et al., 2003), one might expect movement differences between positions post the peak intensity period of competition. It is likely that several situational and match-related contextual factors are contributing to the lack of positional activity profile differences post the peak periods of matches, with individual player fatigue not the only culprit. For example, given higher intensity activities are often aligned with goal/try scoring (Faude et al., 2012; Gabbett et al., 2016), and post scoring reviews often occur before one player takes a conversion kick, both positions movement are likely equally reduced during these "rest" periods.

Accelerometer-derived PlayerLoad™ detected the majority of substantial positional differences post peak periods, indicating improved sensitivity compared to GPS-derived measures in doing so. In congruence, accelerometers outperformed GPS in quantifying positional and match-half differences in player peak intensities during professional rugby union competition (Chapter 3). Where substantial positional differences occurred, PlayerLoad™ was greater for forwards vs. backs (ES: 0.3-1.5), whilst GPS-derived mean speed and metabolic power was greater for backs vs. forwards (ES: 0.3-1.7). Given accelerometer-derived PlayerLoad™ displayed improved sensitivity in quantifying positional differences during and post peak periods of rugby competition, we recommend the use of accelerometers alongside GPS technology. Findings suggest that GPS-derived measures of mean speed and metabolic power were sensitive to detecting fluctuations in player movement for backs, whilst PlayerLoad™ was more sensitive to detecting movement fluctuations of forwards and detecting positional pack differences.

Metabolic power and PlayerLoad™ consistently quantified larger exercise intensity declines post peak periods of competition when compared to mean speed. Consistent with our findings, relative distance (i.e. mean speed) underestimated the intensity of peak periods of rugby sevens competition when compared to metabolic power (Furlan et al., 2015). Theoretically these findings make intuitive sense, as the metabolic power model (Osgnach et al., 2010) considers both speed and acceleration, whereas relative distance/mean speed only quantifies the velocity of movement. Further, movements that incur little horizontal displacement (e.g., collisions, tackles and many sport-specific movements) are likely underestimated by GPS (Boyd et al., 2013). Accelerometers that quantify tri-axial accelerations at much higher sampling frequencies than GPS evidently quantify a greater proportion of player rapid acceleratory movements that incur little horizontal displacement. By being able to quantify more of what rugby players physically do (external load), accelerometer- derived PlayerLoad™ and GPS-derived metabolic power displayed improved sensitivity in quantifying exercise intensity fluctuations compared to a speed-based metric. Present findings are in support of others (Delaney et al., 2016a; Furlan et al., 2015) in recommending the use of acceleration-based indices alongside speed-based metrics to measure the external load of rugby players.

6.5 Practical Applications

- Real-time declines in player movement post intense periods of competition may inform coach tactical decisions such as player positional changes, team formation changes and player substitutions.

- Activity profile data post peak periods of competition may inform match-specific high-intensity interval training (HIIT) prescription, programming for both high-intensity periods and for "active recovery" periods between efforts using game-based methodologies such as small-sided games.
- The right tool needs to be used for the job. Accelerometers were better able to detect positional movement differences between forwards and backs post peak periods. GPS-derived measures of mean speed and metabolic power were more sensitive to detecting fluctuations in player movement for backs, whilst PlayerLoad^{TM} was more sensitive to detecting movement fluctuations of forwards.
- Both speed- and acceleration-based measures should be used to quantify the external load of rugby players.

6.6 Conclusions

This study was the first to sequentially track the time-course of exercise intensity declines post the most intense periods of team sport competition using GPS and accelerometry. Mean speed, metabolic power and PlayerLoad^{TM} declined sharply (~ 29-86%) post the most intense 5-600 seconds of professional rugby competition, with the magnitude of decline principally dependent on the peak intensity attained during any given period. Post the most intense periods of rugby competition, exercise intensity declined below the average match-half intensity 81% of the time and rarely returned to or exceeded it. Typically, exercise intensity declines post the peak intensities of competition were similar between match-halves, positional groups and levels of rugby competition. Accurate identification of the peak exercise intensities of competition using rolling epoch analysis with five duration-matched sequential periods post has improved limited understanding of rugby player fatigue and pacing strategies, which may inform tactical match decisions and match representative training prescription and monitoring.

CHAPTER 7: STUDY 5 - MODELLING PROFESSIONAL RUGBY PEAK INTENSITY-DURATION RELATIONSHIPS USING POWER LAW

7.1 Introduction

Human beings are principally nonlinear organisms that rely on complex interactions between many physiological feedback systems (Higgins, 2002; Katz et al., 1994). Power law describes a nonlinear yet dependent relationship between two variables (x and y), where one variable (y) changes as a fixed power (exponent) of another (x). The parameters of power law relationships are used to make inferences about processes underlying phenomena, to test theoretical or mechanistic models, and to estimate and predict patterns or processes that are outside of and beyond the scope of observed experimental data (White et al., 2008).

Power law analysis has been recently applied in professional soccer (Delaney et al., 2017b; Lacome et al., 2018) and in rugby league (Duthie et al., 2017) to quantify peak intensities and the rate of peak exercise intensity decline as a function of time during competition (Delaney et al., 2017b) and training (Lacome et al., 2018). Power law analysis has also been used to assess youth soccer (Duthie et al., 2018) by age and position and evaluate the relationship between physical performance tests and peak intensities achieved during rugby league competition (Duthie et al., 2017). Power law may be practically applied in team sports to improve match-specific exercise intensity prescription and monitoring for any given exercise duration, using specific game-based methodologies, such as small-sided games (SSG) (Delaney et al., 2017b; Lacome et al., 2018).

Using wearable Global Positioning Systems (GPS) and rolling average epoch analysis (Varley et al., 2012a) to quantify peak intensities of professional soccer competition, speed- and acceleration-based measures exhibited almost perfect linear declines with increasing exercise durations of 1-10 minutes when log-transformed (r = 0.97-0.98), displaying power law characteristics (Delaney et al., 2017b). Likewise, power law log-log plots have been able to accurately estimate exercise intensity-duration relationships (r = 0.94-1.0) across three exercise measures (total distance, high-speed distance and mechanical work) between professional soccer matches and SSGs (Lacome et al., 2018). However, no team sport study to date has examined the standard errors of power law regression model estimates. Improved understanding of model errors may enhance or reduce confidence and use of power law for estimating/modelling match-specific exercise intensities for any given training drill duration.

Rates of decline in running intensity as a function of time were similar between professional soccer playing positions, with trivial to small differences observed (Delaney et al., 2017b). Similarly in youth soccer, there were no substantial differences between playing levels in the decline in running intensity as exercise duration increased (Duthie et al., 2018). In contrast, exercise intensity differences between professional soccer matches and SSG training were highly playing position and SSG type (4v4, 6v6, 8v8 and 10v10) dependent, irrespective of rolling average duration (Lacome et al., 2018). Further, in professional rugby league there were large negative correlations between a player's physical qualities (maximum speed and relative squat strength) and the rate of decline in running speed and metabolic power during competition (Duthie et al., 2017). Rates of peak intensity decline as a function of exercise duration have yet to be examined with power law models incorporating rolling epoch durations of less than 1 minute. No study to date has investigated team sport peak intensity-duration power law characteristics using accelerometer and match-half data. Chapters 3, 4, 5 & 6 revealed accelerometers provide meaningful additional information to GPS technology that may aid practitioners in physically preparing and monitoring team sport athletes, warranting examination using power law. Lastly, whether the power law relationship can accurately predict/model exercise intensities as a function of time in both elite and sub-elite rugby union (rugby) that have higher collision and stoppage frequencies, limiting "free running" time compared to other football codes is still unknown. The purpose of the present investigation was to establish whether power law models could accurately predict/model the peak intensities of rugby competition as a function of time.

7.2 Methods

This study represents an extension of Chapter 4. Consequently, only the novel methodologies pertaining to power law modelling and statistical analysis are presented.

7.2.1 Power Law Modelling

To estimate the decline in match exercise intensity as exercise duration increased, each measure of exercise intensity (i.e. mean speed, metabolic power and PlayerLoad™) was assessed relative to the rolling average 5-600 second duration as a power law relationship (Katz et al., 1999; Katz et al., 1994; Kennelly, 1906). Power law models applied to human locomotion: $y = cx^n$ (equation 1) that compare running times (y) and distances (x), yield positive constants (i.e. c and n are positive values), meaning increased running distances result in increased running times. However, when plotting running speed and/or acceleration measures against running time, the inverse is true for the exponent (i.e. speed/acceleration decreases with increased running time). A plot of log (y) against log (x) results in a straight line with slope *n* and an intercept of c^e (Katz et al., 1994) (Figure 7.1). Linear regression produced values for slopes and intercepts for each measure (mean speed, metabolic power and PlayerLoad™), for each player's match-half file. The exponential of the intercept was calculated, creating a prediction equation of running intensity (*i*) as a function of time (*t*), using the power law equation:

$$i = ct^n$$

$$Intensity = Intercept \times (Time)^{Slope}$$

The intercept established from the power law relationship reflects the theoretical highest intensity that occurs during competition as time approaches zero (Delaney et al., 2017b; Lacome et al., 2018). Although much higher running intensities can be reached in isolated running drills (Lacome et al., 2018), the intercept values reported can be used as match-specific references when prescribing and monitoring training activities incorporating both technical and tactical development (e.g. SSGs and game-specific drills) (Duthie et al., 2018). The slope represents the rate of decline in peak exercise intensity as exercise duration increases.

Figure 7.1 provides an example of the calculation of the power law relationship for an individual, where the mean speed ($m.min^{-1}$) is plotted as a function of time, whilst the predicted values from the log-transformed data are presented by the regression line/curve. The close relationship between the predicted and actual data displayed in Figure 7.1 illustrates the "goodness of fit" of the power law model and provides support for its use. Individual player files were then grouped by broad playing positions (forwards, backs), match-half (first, second) and level of competition (elite: Super 15 Rugby, sub-elite: National Rugby Championship) to create a power law modelling framework for each of the three measures of exercise intensity. Power law models were chosen instead of hyperbolic models such as the critical power model (Hill, 1993) for a few reasons. First, power law models are simpler: the exponent from power analysis has been shown to be correlated to speed at critical power/maximal aerobic speed in elite runners (Zinoubi et al., 2017). Practitioners are likely to use models that are simpler to both compute and understand. Second, critical power models typically used in individual sports such as cycling collect power-time datum via several independent exercise tests. Conversely, power law exponential functions usually characterise continuous temporal processes where the value of a datum is dependent on the value of its predecessor (Burnley et al., 2016), with dependence likely using team sport data sets. Third, to validly apply the critical power model during collision-based intermittent sports like rugby would require modelling each individual athlete's: critical power, amount of finite work capacity available above critical power (W') and their time constants to recover W' (Skiba et al., 2012; Vanhatalo et al., 2011). These modelling procedures were beyond the scope of the present investigation, but do provide an exciting avenue for future research applying critical power to team sport contexts. Lastly, in rugby, the declines in exercise intensity with increasing exercise duration may be largely determined by contextual factors such as stoppages, e.g. refereeing decisions and point scoring occasions (Delaney et al., 2016a). Large proportions of stoppage time decreases player work-to-rest ratios, potentially limiting the application of the critical power model as anaerobic work capacity may not be seriously challenged in rugby (Vanhatalo et al., 2011).

7.2.2 Statistical Analysis

Each of the three measures of maximum mean movement were analysed with the general linear mixed modelling procedure (Proc Mixed) in SAS. The measures were log-transformed prior to analysis to reduce non-uniformity of error (Hopkins et al., 2009). The fixed effects in the model were player position (backs, forwards) interacted with match-half (1st, 2nd), interacted with time on the field to adjust for this variable. Mean time on the field for each player in each half was re-scaled to zero to avoid adjusting the peak intensities to a grand mean time on the field for positions and halves. This re-scaling enabled better quantification of positional (forwards vs backs) and match-half (1st half vs 2nd half) mean differences. Match identity was the only random effect in the model. Player identity was not included as a random effect unlike other power law investigations (Delaney et al., 2017b; Duthie et al., 2017). In previous studies (Delaney et al., 2017b; Duthie et al., 2017) authors have derived a standard error of the estimate for each subject separately and then presented an average SEE. However, this approach underestimates the error when there are real differences between individuals in the slopes and intercepts, which there are. The general linear mixed modelling process was repeated for elite and sub-elite levels of rugby competition. Each model produced an intercept and slope that gave the line of best fit for the log intensity, log duration transformed least squares mean data (Figure 7.1), as well a standard error of the estimate for each positional group and match-half, across each of the three measures (Tables 7.1 & 7.2). Power law model goodness of fit was assessed using coefficients of determination (R^2), with the following scale for the square root of $R^{2,}$ correlation coefficient (r): < 0.1 trivial, < 0.3 small, < 0.5 moderate, < 0.7 large, < 0.9 very large and > 0.9 almost perfect (Hopkins, 1997). The SEE expressed the root mean square error of each power law model, enabling quantification of the accuracy of each model's predictions through examination of the scatter of points about the regression line (Hopkins, 1997). Residual vs. predicted plots were generated for each measure and level of competition (individual player prediction error, not by position and match-half) to assess not only the average model error (SEE), but to assess exercise intensity prediction error across all 5-600 second exercise durations (Figure 7.3).

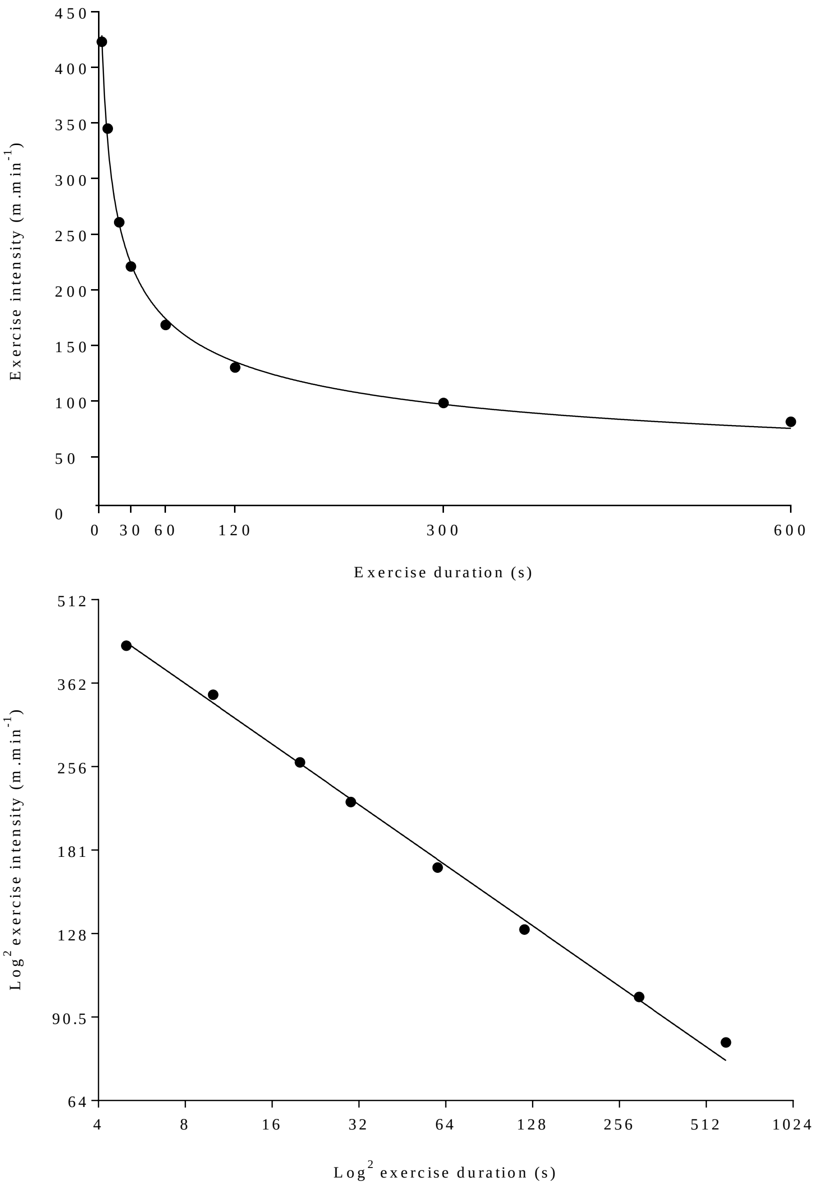


Figure 7.1 Example of power law analysis modelling the relationship between professional rugby exercise intensity: mean speed (m.min^{-1}) plotted for each rolling average exercise duration of 5-600 seconds. The power curve represents predicted exercise intensity values as a function of time. If the raw mean speed (m.min^{-1}) and duration are logged, a linear relationship results, permitting the calculation of y intercepts and slopes.

7.3 Results

The log of peak exercise intensity (i.e. mean speed, metabolic power and PlayerLoad™) and log of exercise duration (5-600 s) displayed almost perfect power relationships (R^2 = 0.969 to 0.993) for elite and sub-elite rugby backs and forwards and during the first and second match-halves (Tables 7.1, 7.2 and Figure 7.2). The standard errors of the estimates for the prediction models ranged from 5 - 9.7% (mean 7.5%) and 4.1 - 12% (mean 8.3%) for elite and sub-elite rugby respectively (Tables 7.1 & 7.2). Residuals vs. predicted values revealed unequal variance along the regression lines (bimodal 'U' shaped heteroscedasticity), indicating power prediction models typically underestimated shorter (5 to 10 s) or longer (300 to 600 s) exercise intensities and overestimated 20 to 120 second intensities (Figure 7.3), by up to ~ 20-25%.

The *y* intercepts (analogous to 1-second theoretical peak intensity) were greater for backs than forwards for mean speed, metabolic power and PlayerLoad™ by 20%, 28% and 14% respectively during elite rugby and by 14%, 34% and 25% respectively during sub-elite rugby (Tables 7.1 & 7.2). The rate of decline in peak intensity as duration increased (slope) was also greater for backs than forwards for mean speed, metabolic power and PlayerLoad™ by 6%, 6% and 11% respectively during elite rugby and by 13%, 14% and 15% respectively during sub-elite rugby (Tables 7.1 & 7.2). The *y* intercepts and slopes were typically similar between match-halves and levels of rugby competition.

Table 7.1 Intercepts and slopes to predict peak exercise intensity of Elite Super Rugby competition using power law.

	Half	Intercept	Slope	Error (%)	R^2
Mean speed ($m.min^{-1}$)					
Backs	1st	748	-0.355	5.0	0.993
	2nd	716	-0.356	5.1	0.993
Forwards	1st	602	-0.332	5.9	0.989
	2nd	571	-0.334	5.6	0.990
Metabolic power ($W.kg^{-1}$)					
Backs	1st	118	-0.412	6.8	0.991
	2nd	116	-0.417	7.0	0.990
Forwards	1st	85	-0.374	8.5	0.983
	2nd	83	-0.382	8.8	0.982
PlayerLoad™ (au)					
Backs	1st	7.1	-0.402	9.5	0.981
	2nd	7.1	-0.405	9.7	0.981
Forwards	1st	6.3	-0.363	9.4	0.978
	2nd	5.9	-0.352	8.4	0.981

Power law equation: Predicted intensity = Intercept × (Duration of interest in seconds)^{Slope}

Goodness of model fit was evaluated by the standard error of the estimate and R-squared values.

Table 7.2 Intercepts and slopes to predict peak exercise intensity of sub-elite National Rugby Championship competition using power law.

	Half	Intercept	Slope	Error (%)	R^2
Mean speed ($m.min^{-1}$)					
Backs	1st	742	-0.349	8.7	0.979
	2nd	747	-0.356	9.5	0.976
Forwards	1st	541	-0.298	4.1	0.993
	2nd	557	-0.316	8.3	0.976
Metabolic power ($W.kg^{-1}$)					
Backs	1st	122	-0.415	8.7	0.985
	2nd	111	-0.408	12	0.973
Forwards	1st	77	-0.349	8.8	0.979
	2nd	76	-0.360	11	0.969
PlayerLoad™ (au)					
Backs	1st	7.3	-0.407	8.3	0.986
	2nd	6.9	-0.400	8.6	0.984
Forwards	1st	5.3	-0.335	5.3	0.991
	2nd	5.4	-0.354	6.8	0.987

Power law equation: Predicted intensity = Intercept × (Duration of interest in seconds)^{Slope}

Goodness of model fit was evaluated by the standard error of the estimate and R-squared values.

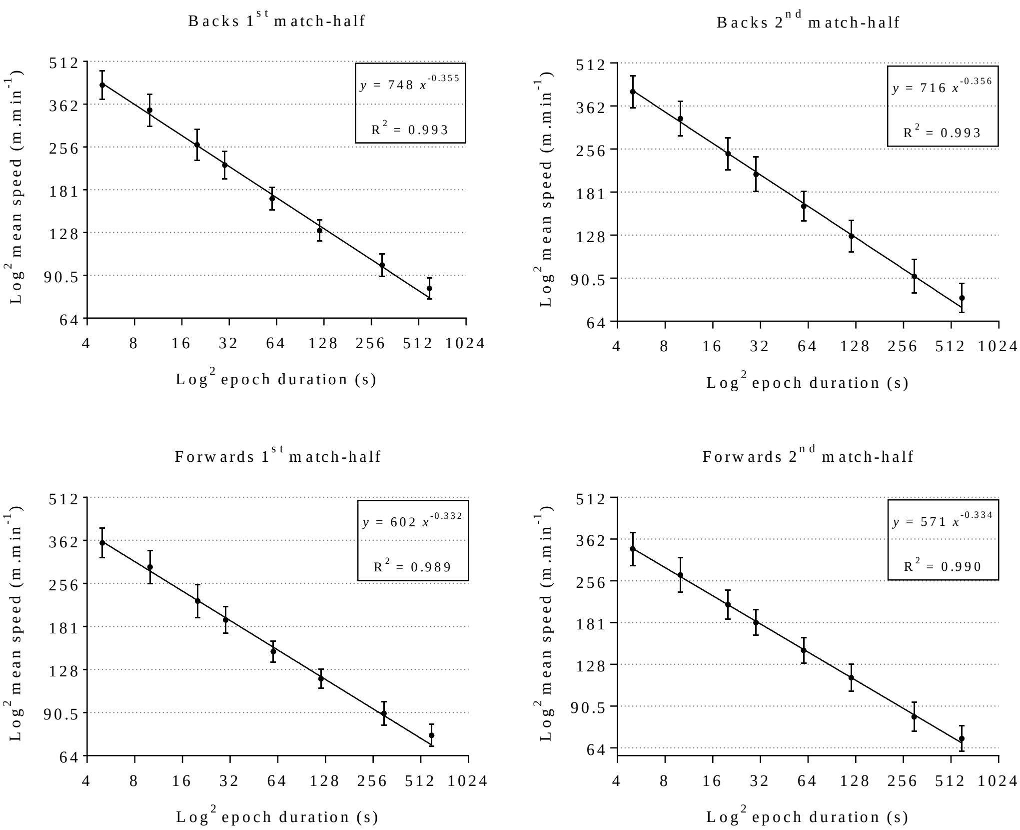


Figure 7.2 Elite Super 15 Rugby log-log mean speed-epoch duration power law relationships by playing positon and match-half.

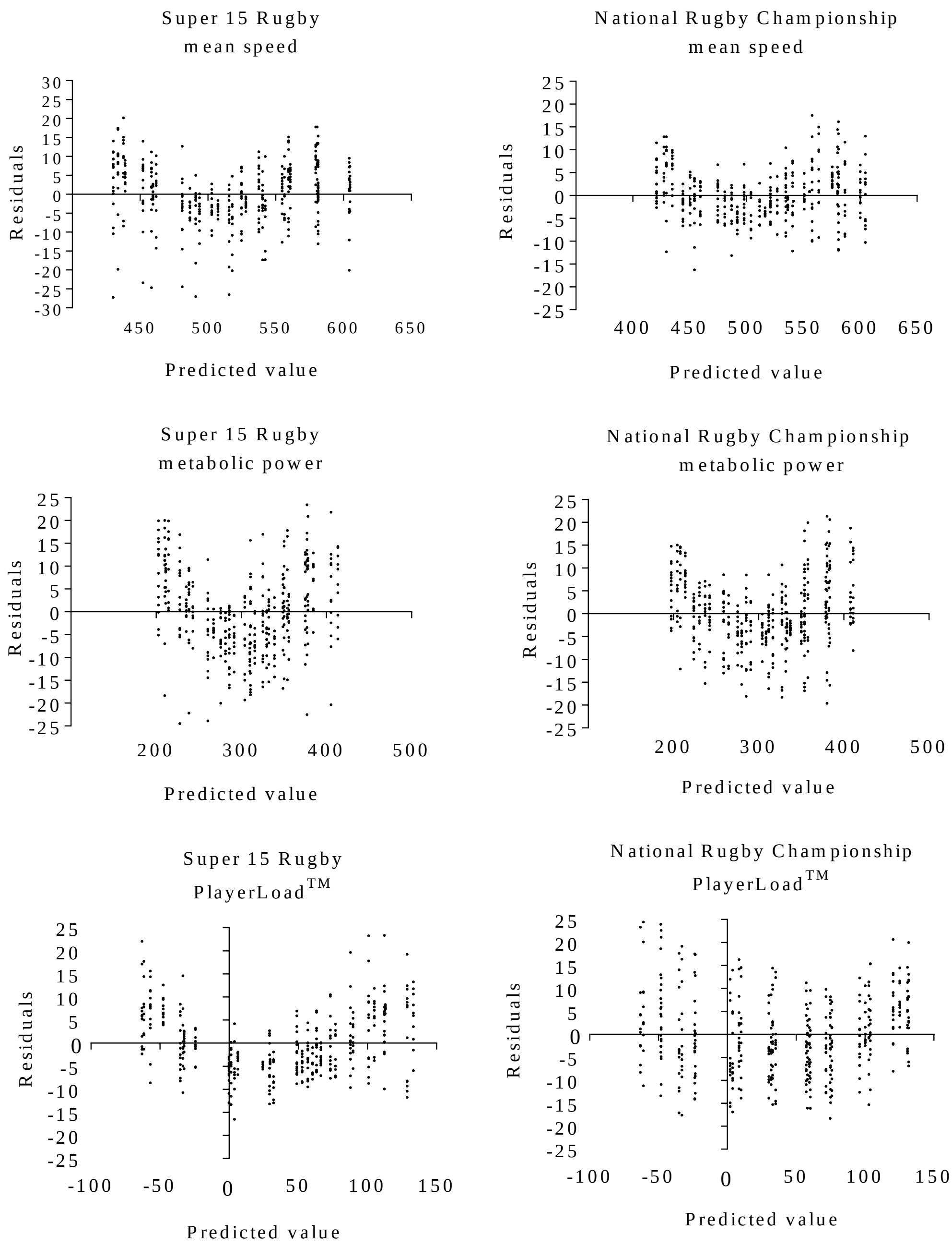


Figure 7.3 Individual player residuals vs predicted values for 5 to 600 second exercise intensities, for each measure of exercise intensity across both levels of rugby competition. Predicted values are 100 × the natural log. Residuals can be interpreted as approximate percents (%).

7.4 Discussion

The purpose of the present investigation was to establish whether power law models could accurately predict the peak intensities of rugby competition as a function of time. This study was the first to demonstrate that professional rugby union peak intensities of competition can be accurately predicted from exercise duration using power law (R^2 = 0.97-0.99), irrespective of playing position, match-half, level of competition or measure of exercise intensity. These findings advance the practical application of power law models in team sports by providing novel insights on model prediction typical error as well as the patterns of error as a function of time. Power law models had a typical exercise intensity prediction error of 7.5% and 8.3% for elite and sub-elite rugby respectively, across 5 to 600 second exercise durations. Prediction models typically underestimated shorter (5-10 s) and longer (300-600 s) duration peak exercise intensities and overestimated 20-120 s exercise intensities, by up to ~ 20-25%. The present findings support the use of power law models in team sports to improve match-representative exercise intensity prescription and monitoring for any given exercise duration, using specific game-based methodologies, such as small-sided games. However, practitioners should be aware of prediction model errors when interpreting, prescribing and monitoring match-specific exercise intensities for any given training drill duration.

The present investigation extends on recent football power law investigations (Delaney et al., 2017b; Duthie et al., 2017; Lacome et al., 2018) that incorporated individual athletes as a random effect in their linear mixed models. By doing this, these prediction models reported exercise intensity predictions as a function of time for a given match within a competitive season. Such analysis is very useful to predict and understand match-to-match variation in peak intensities of competition. However, better ‘ground truth’ exercise intensity predictions for training prescription and monitoring purposes are yielded by using each player’s season long mean peak intensities of competition, across all matches for each duration analysed (e.g. 5-600 s). By doing this, the power models in the present study give more realistic estimates and standard errors of the estimates for a given individual for exercise intensity prediction purposes.

Power law models are capable of accurately modelling exercise intensities as a function of time during professional soccer (Delaney et al., 2017b; Lacome et al., 2018), rugby league (Duthie et al., 2017) and now rugby union competition, with almost perfect correlations (0.90-0.99). However, model prediction typical error of 4.1-12% and heteroscedastic residuals of up to ± 25% for peak 5-600 second exercise intensities of professional rugby indicate power law models are far from perfect. Power law models applied to individual sports such as running observed prediction errors of 3-6% for 200-2000 m running times (Katz et al., 1999). Hyperbolic models incorporating metabolic energy yielding processes reduced absolute error between predicted and actual Olympic Games running times to 0.86% for distances of 100 to 10,000 m (Ward-Smith, 1985) and reduced world record running time prediction error to 0.73% for 60-42,000 m events (Péronnet et al., 1989). Several differences between individual sports (e.g. running, cycling and swimming) and team sports may explain reduced nonlinear model prediction errors in the former. Team sports are multi-directional, intermittent and chaotic in nature, often with substantial physical contact elements and stoppages in play. These factors mean that exercise duration cannot possibly explain all of the variance in peak exercise intensity during team sports such as rugby. The complexities of team sport movement dictate that power law models will inevitably display better goodness of fit and lower prediction errors for individual sports, being able to explain greater variance in exercise intensity with changes in exercise duration. We recommend that practitioners quantify and understand the error and limitations associated with power law prediction models to aid their interpretation and use of such models for training prescription and monitoring purposes in team sports.

Knowledge of the most intense passages of competition allows coaches to train players in a match-specific or representative manner. The power law equations of the present investigation (Tables 7.1 & 7.2) provide rugby coaches with an ability to predict both speed and acceleration based peak match intensities for both elite and sub-elite players across any duration of interest. For instance, if a coach wanted to know the peak 60 second speed of elite rugby backs in the first match-half they could use equations in Table 7.1 to predict this [e.g. peak mean speed = 748 m.min^{-1} × (60 seconds)$^{-0.355}$]. The result is a peak 60 second mean speed of 175 m.min^{-1} (equivalent to 2.9 m.s^{-1} or 10.5 km.h^{-1}), which may be used to prescribe and monitor the intensity of sport-specific training.

The power law model intercepts and slopes presented here are not directly comparable with other investigations (Delaney et al., 2017b; Duthie et al., 2018; Duthie et al., 2017; Lacome et al., 2018) due to novel investigation of durations less than 1 minute, resulting in present models having larger intercepts and slope declines. Thus, power law prediction models (Tables 7.1 & 7.2) were used to predict the 60 second peaks, which can be directly compared to the 60 second intercepts of previous football code research (Table 2.4) for mean speed and metabolic power that are common measures amongst published studies. The peak 1 minute mean speed of elite and sub-elite professional rugby (145-175 m.min^{-1}) was lower than rugby league (Duthie et al., 2017) and national and youth soccer (Delaney et al., 2017b; Duthie et al., 2018), yet similar for international soccer (Lacome et al., 2018) (Table 2.4). The generally lower peak mean speed observed in professional rugby compared to the other football codes is likely due to increased collision-based elements (e.g. tackles, rucks, mauls, scrums, lineouts etc.) obstructing free running (Duthie et al., 2003). Metabolic power 1 minute peaks (17-22 $W.kg^{-1}$) were typically similar between professional rugby and other football codes (Table 2.4), with the upper range limits (22 $W.kg^{-1}$) exceeding professional rugby league and soccer, yet falling below elite youth soccer (Duthie et al., 2018). Considering metabolic power accounts for both speed and acceleratory movements and rugby players produced lower peak speeds, accelerations must have accounted for a greater proportion of metabolic power during rugby compared to rugby league and soccer. Whilst speculative, greater peak speed and metabolic power intercepts observed during youth elite soccer (Duthie et al., 2018) compared to all professional football codes (Table 2.4) may be due to reduced defensive structures and strategies employed in combination with reduced frequency and magnitude of collision-based movements.

Elite and sub-elite rugby backs produced greater mean speed, metabolic power and PlayerLoad™ intercepts than forwards by 14-34% (Tables 7.1 & 7.2). Similarly, in rugby league, forward positions (edge forward and hooker) produced the lowest peak mean speed and metabolic power intercepts respectively, whilst fullbacks produced the greatest peak values of all positions (Duthie et al., 2017). In support of our findings, rugby backs typically produce greater intensity of movement than forwards over shorter durations as they are required to evade opponents with rapid acceleration, change of direction and/or maximal speed to score tries or chase down and tackle opponents to deny try scoring (Quarrie et al., 2013).

The decline in peak exercise intensity as time increased (slope) was greater for rugby backs than forwards (6-15%). In rugby league, large negative correlations between a player's physical qualities (maximum speed and relative squat strength) and the rate of decline in running speed and metabolic power have been observed during competition (Duthie et al., 2017). Rugby backs also demonstrate superior anaerobic power and muscle strength relative to body weight when compared to forwards (Duthie et al., 2003). The steeper slope decline of exercise intensity for backs in the present study may be due to faster player's (typically backs), having a higher proportion of fast twitch muscle fibres, that have reduced fatigue resistance over longer exercise durations (Trappe et al., 2015). Perhaps professional rugby backs also display negative correlations between physical speed/acceleratory qualities and slope declines as exercise duration increases, with future research warranted to confirm this. In contrast to rugby findings, slope declines have been shown to be similar across professional soccer positions (Delaney et al., 2017b), potentially due to match stoppages (e.g. referring decisions, set piece, substitutions etc.) influencing player movement similarly or due to all players receiving the same training stimulus. The intercept and slope values generated from the present investigations power law analysis highlight the need for rugby training prescription and monitoring to be position-specific but not necessarily match-half or level of competition specific due to typically negligible differences. Speed and acceleratory slope results also highlight the need to vary the volume of time players are exposed to match intensities during training, to improve their ability to repeat and maintain exercise intensities for longer periods of time.

The main limitation of the present investigation is that the power law models only considered exercise duration in its predictions of peak exercise intensity. Prediction models were constructed by playing position, match-half and level of professional rugby, however future research should consider methods that attempt to capture the little yet potentially meaningful unexplained variance from power law models. For example, future nonlinear power or hyperbolic models that can validly incorporate match contextual factors (e.g. stoppages) and individual physical/physiological parameters (e.g. metabolic energy contributions) will likely improve model goodness of fit, homoscedasticity and prediction error.

7.5 Practical Applications

Rugby coaches may use power law to predict peak speed and acceleration based exercise intensities for any duration of interest to prescribe and monitor match-specific training. For instance, when prescribing a small-sided game aiming to replicate the most intense periods of matches, using Tables 7.1 or 7.2 coaches can predict intensity by inputting intercept, time and slope values into the equation: Intensity = Intercept × $(\text{Time})^{\text{Slope}}$. If a coach wished to overload mechanical loading of elite forwards during a 5-minute (300 s) training drill, PlayerLoad™ could be solved for using values in Table 7.1: PlayerLoad™ = $6.3 \times (300\ \text{s})^{-0.363}$. This results in a predicted PlayerLoad™ match intensity of 0.8 au/second or 240 au across the 5 minute drill. Practitioners should be aware that there is error associated with exercise intensity prediction models and incorporate this typical error (4.1-12%, Tables 7.1 & 7.2) into their interpretation and use of them. In relation to the generalisability of the present findings, previous investigations have used power law and found relative distance (m.min^{-1}) and average acceleration/deceleration (m.s^{-2}) intercept and slope differences between football codes (i.e. AFL, rugby league, rugby union and soccer) and between playing positions within codes (Delaney et al., 2016b). Our comparable rugby union relative distance intercept and slope values differ vastly from previous investigations (Delaney et al., 2016b), namely due to the calculation of time measured in seconds as opposed to minutes in our power law models given we calculated peak 5 s to 600 s peak intensities of competition. Using Delaney and colleagues (Delaney et al., 2016b) relative distance mean intercept (169 $m.min^{-1}$) and slope (-0.29) values for rugby union backs, if prescribing a 5 minute training drill their predicted relative distance intensity would equal: $Intensity = 169\ m.min^{-1} \times (5\ minutes)^{-0.29}$, that comes to 106 $m.min^{-1}$. Using the present investigations comparable rugby union backs and power law model that calculated time in seconds (i.e. 5 minutes = 300 seconds) our predicted relative distance would equal: $Intensity = 748\ m.min^{-1} \times (300\ seconds)^{-0.35}$, that comes to 99 $m.min^{-1}$. This power-law prediction difference of only 6 $m.min^{-1}$ between the two rugby union studies demonstrates that our findings are somewhat generalisable if comparing to similarly trained elite rugby cohorts within the same positional group. Between 4-6 specific positional groups within each of four football codes, relative distance intercepts (theortical peak intensity) tended to fluctuate by no more than 31 $m.min^{-1}$, with the smallest positional intercept differences observed in rugby league (13 $m.min^{-1}$ range across 6 positions) and rugby union had the largest positional intercept differences of all football codes (31 $m.min^{-1}$ range across 4 broader positional groups). These findings are likely due to the fact that rugby league positional anthropometrics and physiological capacities are typically more homogeneous compared to rugby union playing positions that are more heterogeneous. Whilst findings may be somewhat generalisable to football athletes of similar training status within the same code and positional group, we advise each team to use power law to calculate exercise intensity as a function of time for their specific cohort of interest.

Coaches can concurrently train physical, technical and tactical sporting elements by using match- and position-specific peak exercise intensities reported in the present study. Coaches can manipulate the number of players, field dimensions and rules of training drills to over or underload the speed and/or acceleratory demands as desired, whilst monitoring player training intensities relative to peak match intensities (%). Training time spent below, at or above 'match intensity' could be quantified and monitored to help periodise training programs and to better understand player internal load responses to external training loads. If players are unable to achieve peak intensities of competition during game-based training, they may not possess the underlying physiological capacity needed to effectively perform their tactical roles during competition and therefore may benefit from isolated physical development. On the other hand, if players are able to achieve peak intensities of competition during training, they can be progressively overloaded in a periodised manner by repeated exposures to such intensities to further improve their physiological qualities.

7.6 Conclusions

This study was the first to demonstrate that professional rugby union peak intensities of competition can be accurately predicted from exercise duration using power law, irrespective of playing position, match-half, level of competition or measure of exercise intensity. Present findings have advanced the practical application of power law models in team sports by providing novel insights on model prediction typical error as well as the patterns of error as a function of time. Results support continued use of power law models in team sports to improve match-representative exercise intensity prescription and monitoring using specific training methodologies. However, practitioners should be aware of prediction model errors when interpreting, prescribing and monitoring match-specific exercise intensities for any given training drill duration.

CHAPTER 8: GENERAL DISCUSSION

8.1 Thesis Synopsis

The series of five novel studies presented within this thesis (Figure 8.1) have identifed, quantified and characterised the most intense periods of professional rugby competition and periods thereafter. The main aim and practical application of this research was to help coaches prescribe and monitor training that is more representative of the peak periods of competition and to aid match-day tactical decisions. The final section of the thesis will provide discussion of original research (Chapters 3 to 7), research progression, practical applications, limitations, future directions and conclusions.

8.1.1 Use the right tool/s for the job

In both research and practice, accelerometers are grossly underutilised compared to GPS for quantifying, monitoring and prescribing the peak periods of team sport competition. This is surprising given the reduced accuracy of GPS for quantifying high-velocity and acceleratory movements that frequently occur in team sports (Boyd et al., 2013; Jennings et al., 2010; Rawstorn et al., 2014). In a recent systematic review investigating the use of microtechnology to quantify the peak match demands of football codes (Whitehead et al., 2018b), only 2 of the 27 studies (7%) that met author's eligibility criteria used accelerometer-derived metrics such as PlayerLoad™ or BodyLoad™, whilst GPS-derived relative distance was reported in 63% of studies. This series of studies adds considerably to the body of knowledge on the application of accelerometers to quantify physically intense periods of football competition.

Study one (Chapter 3) found that accelerometers outperformed GPS in quantifying positional and match-half peak intensity differences during rugby competition, identified using rolling epoch analysis. Relative to professional rugby backs, the forwards produced greater PlayerLoad™ per unit of distance covered or metabolic power generated. This finding is in line with forwards spending more time in physical contact with the opposition and completing more total work throughout a match than backs (Duthie et al., 2003). If team sport performance staff were to solely use GPS technology to quantify and monitor activity profile differences between players and positions, many frequently occurring movements that incur little horizontal displacement (e.g., collisions, tackles, jumping, change of direction etc.) would be underestimated. Misrepresentive quantification of physical movement during matches and training may lead to training workload errors, maladaptation or heighten the likelihood of illness or injury.

Accelerometers and GPS provided different results fundamentally because accelerometers measure player movement in three dimensions (x, y & z) including vertical displacement, whereas GPS technology only measures player movement in two dimensions (x & y, i.e. forwards-backwards and side-to-side). Further, accelerometers sampling rate was ten times that of the GPS receivers used (100 Hz vs 10 Hz), enabling more accurate quantification of rapid movements. As most team sports involve many movements comprising both vertical and horizontal displacement across a broad range of speeds, both technologies should be used. It is recommended that football practitioners and researchers select technologies and measures depending on the primary sporting movements and questions of interest (i.e., use the right tool for the job).

It was clear from the pattern of positional differences across 5 to 600 second epoch durations, match-halves and levels of competition in Chapters 3 & 4 that GPS and accelerometer measures provided different information about rugby union player movement. These findings demonstrate that use of either GPS or accelerometers in isolation is inadequate to accurately quantify all forms of rugby union external load. Both chapters 3 & 4 findings support a recent training load monitoring framework for team sports that separates physiological and biomechanical load-adaptation pathways (Vanrenterghem et al., 2017). This framework uses an analogy of a car to describe the physiological vs biomechanical external load that team sport athletes experience. The physiological load component can be viewed as a car engine with GPS time, distance and speed derivatives providing an estimate of "fuel" in the player's "engine", facilitating monitoring of external work to estimate internal energy demands or metabolic load (e.g., glycogen depletion, heart rate). Whereas biomechanical load refers to external work performed by the body's soft tissues (e.g., muscles, bones and ligaments, analogous to a car's suspension) against the ground and other player's during impact, that can be estimated in the field with highly responsive motion sensors such as accelerometers. Chapter 4 findings imply that neither accelerometer nor GPS measures should be used a proxy measure for the other, as they measure different external load constructs (biomechanical and physiological load respectively). If football performance staff wish to accurately detect duration-, position- and half-specific differences in player activity profiles during the most intense periods of competition, both speed and acceleratory indices derived from both GPS and accelerometer technology should be used.

8.1.2 Understand the utility & limitations of technology

Study two (Chapter 4) assessed the sensitivity, reliability and convergent validity of GPS and accelerometer measures for quantifying peak 5 to 600 second intensities of rugby. Innovative insights were garnered on the utility of commonly used GPS and accelerometer measures (mean speed, metabolic power and PlayerLoad^{TM}) for quantifying peak rugby intensities, improving a coach's ability to interpret and use such data to inform practice. Prior to this study, there was no available literature on the sensivity or reliability of these commonly used GPS- and accelerometer-derived measures for quantifying the peak intensity periods of team sport competition. This study provided further evidence that the reliability of team sport movement as measured by both GPS and accelerometers is inversely related to speed of movement. This finding creates a dilemma for practitioners when selecting measures and is in accordance with the suggestion that validity and reliability of a measure is likely inversely related to its importance for external load quantification and monitoring (Akenhead et al., 2016; Buchheit et al., 2017). The poor sensitivity and low reliability of GPS and accelerometer measures implied that rugby players need to be monitored across many matches (approximately one team sport season) to obtain adequate precision for assessing individuals. In professional practice, applied sport scientists must work at a fast pace, interacting with coaches and players to deliver innovative, efficient and effective performance programs (Coutts, 2016). Poor sensitivity and low reliability does not mean that PlayerLoad^{TM}, mean speed and metabolic power measures should not be used to quantify, monitor and prescribe peak intensity periods, but rather suggests that more caution is needed when interpreting individual differences or changes. Defining a larger and more conservative smallest worthile difference (Buchheit, 2016) and/or having more repeated measures are possible practical solutions to this dilemma. The present findings derived from slow research processes has established the reliability, convergent validity and signal to noise of commonly used external load measures, providing quality controlled evidence to support the immediate decision making of fast working practitioners.

8.1.3 Team sport movement is complex & multifactorial

Study three (Chapter 5) examined factors that may influence peak intensities of rugby competition, such as exercise duration, positional group, match-half, level of competition, within-season trends and time spent on field. Findings highlighted that duration- and position-specific player movement data derived from wearable technologies and rolling average analyses may be used as a reference for training monitoring and prescription to objectively prepare players for the most intense periods of competition.

Whilst several studies have provided similar duration- and position-specific peak intensity frameworks across an array of football codes (Delaney et al., 2016a; Delaney, 2016; Delaney et al., 2015; Delaney et al., 2016d), this series of studies was the first to utilise accelerometers in combination with GPS to more adequately quantify totality of team sport movement, use periods less than 1 minute, and quantify peak periods for each match-half, across two levels of football competition. Game based methodologies such as small-sided games may be modified (pitch size, number of players, rules, verbal encouragement) to achieve desired duration- and position-specific physiological and biomechanical external loads whilst simultaneously training technical and tactical skills. For example, larger small-sided game playing areas with less players will facilitate more high-speed running whilst smaller playing areas with more players will facilitate more acceleratory, change of direction and collision-based movements.

The nature of football movement is very complex and relates to a host of contextual factors (Paul et al., 2015), match-related factors (Murray et al., 2015) and individual player characteristics (Kempton et al., 2015a). Chapter 5 explored several factors that may influence the peak intensities of professional rugby competition, yet have received little scientific attention. The majority of comparisons made between the most intense periods of elite versus sub-elite rugby competition yielded unclear or trivial differences, irrespective of duration, position, match-half or measure of intensity used. Within-season declines in peak intensity of competition were more pronounced for sub-elite players compared to elite players and for forwards compared to backs. The most intense 5-600 s passages of elite and sub-elite rugby union competition occurred near the middle of both match-halves on average. Professional rugby players who were on the field longer generally produced greater peak mean speed, metabolic power and PlayerLoad™, with time on field influencing peak intensity to a greater extent in the second match-half compared to the first for both levels of competition.

Knowledge of factors that may influence football activity profiles (Table 2.2) and the magnitude of impact they may have, improves scientific understanding of the complex dynamics of team sport movement. Understanding that team sport movement is multifactorial may inform training and match day practices. For instance, football coaches may alter training drills based on factors known to elicit changes in player movement (e.g. duration, pitch size, number of players, rules etc) to replicate or exceed match-specific peak intensity scenarios. During competition, coaches may use knowledge of other factors such as the influence of time spent of field and positional role on player peak intensities to inform tactical decisions (e.g. substitutions/rotation or formation changes). Altogether, Chapter 5 provides professional rugby coaches with duration- and position-specific intensity frameworks to aid prescription and monitoring of match-specific training, whilst improving broader understanding of factors that influence player movement intensity.

8.1.4 Exercise intensity declines drastically post peak periods of competition

The majority of football time-motion analysis research has used a pre-defined period of time (e.g. 5 min) to identify the peak intensity of competition and comparable periods post (5 min). However, the most intense periods of player movement during a match do not fall completely within pre-defined periods of time, and therefore likely underestimate peak periods and overestimate subsequent periods of activity (Cunningham et al., 2018; Ferraday et al., 2020; Varley et al., 2012a). Therefore, rolling or moving average time period analyses should be used to more accurately identify and quantify the peak periods of football competition and movement thereafter (Varley et al., 2012a).

Studies that have used rolling average analysis to identify the peak period of competition tend to only use one epoch duration to quantify both the peak and post peak periods (Black et al., 2016). Study four of this thesis (Chapter 6) sequentially tracked the time-course of exercise intensity declines post the peak periods of rugby competition using novel analysis. The novel analysis entailed using eight rolling average epoch durations (5-600 s) to identify the peak intensity periods of competition, with five duration-matched intervals used to sequentially track player movement post.

Mean speed, metabolic power and PlayerLoad™ declined sharply (~ 29 to 86%) post the most intense 5 to 600 seconds of professional rugby competition, with the magnitude of decline principally dependent on the peak intensity attained during any given period. Post the most intense periods of rugby competition, exercise intensity declined below the average match-half intensity 81% of the time and rarely returned to or exceeded it. Post peak intensity analysis of different epoch durations, playing positions, match-halves, levels of competiton and measures of exercise intensity were elaborated upon (see Chapter 6). If identical analysis techniques to those in the present study were applied across other football codes, there is no doubt movement intensity would substantially decline post peak periods of competition but to varying extents. In football codes that are of a "stop/start" nature (e.g. rugby, NFL), peak intensities of competition that may be prior to scoring or conceding a try or touchdown are followed by a conversion kick that inevitably reduces post peak period exercise intensity dramatically. In more continuous and "free-flowing" football codes (e.g. soccer, AFL) the reductions in exercise intensity post the peak periods of competition are likely to be less severe. Nonetheless, across all the football codes objective player activity profile data post peak periods of competition may inform tactical match decisions (e.g. substitutions/rotations) and match representative training prescription and monitoring of both "work" and "active rest" periods.

Accurate quantification of player activity profiles post the most intense periods of competition improves limited understanding of team sport athlete pacing strategies and fatigue, which may inform match-day substitution or rotation decisions, player positional changes and team formations. For instance, live player movement data may be collected via GPS receivers and relayed to a receiver antenna connected to a computer, with proprietary software allowing for real-time player movement tracking. If historical data have been collected on the previous peak intensities of competition for a cohort of interest (assuming rolling epoch averages could be programmed into software), it would be possible in real-time to identify similarly intense periods (via pre-defined alerts set within the software). Alternatively, practitioners could use the peak, post peak and average intensities of competition quantified in the present investigation and others (see Table 6.3) as reference values for the football code of interest to set alerts within player tracking software. Consequently, it is possible to identify very intense periods of competition in real-time during matches and quantify inevitable declines in exercise intensity thereafter. Such data may be relayed from the person watching and interpreting the live data stream (e.g. sport scientist) to a coach, ideally providing them with context around the values such as the current match average exercise intensity and/or normative historical values for the team, position or player of interest. Preferably, such activity profile data would be used in conjunction with performance analyst technical key performance indicators to help inform the coach's expert opinions on tactical decisions, such as player substitutions and team formations.

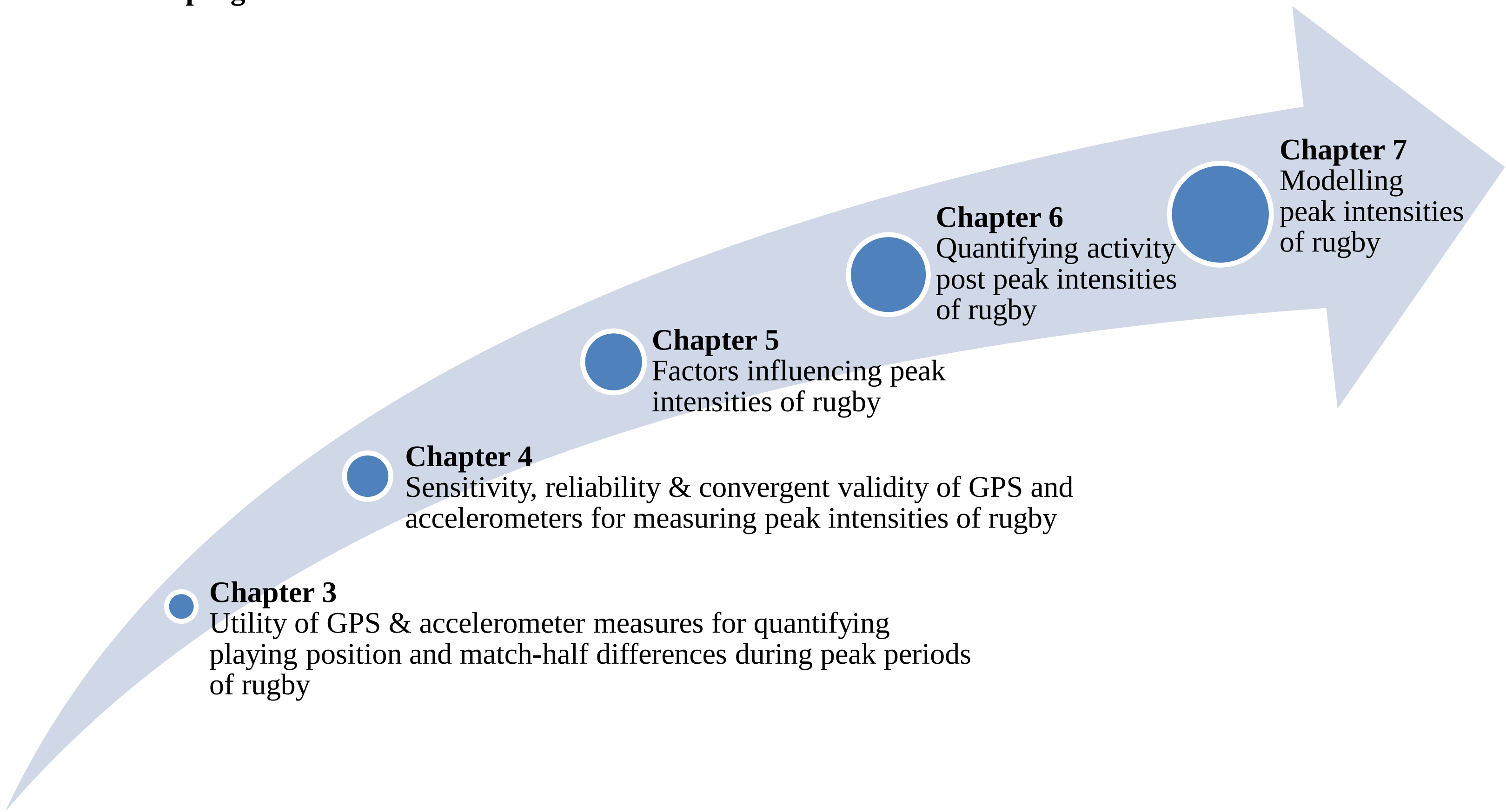
8.1.5 Modelling peak intensities of rugby using power law

Study five (Chapter 7) was the first investigation to demonstrate that professional rugby union peak intensities of competition can be accurately predicted from exercise duration using power law (R^2 = 0.97-0.99), irrespective of playing position, match-half, level of competition or measure of exercise intensity (both GPS and accelerometer derived). Rugby coaches may use power law to predict peak speed and acceleration based exercise intensities for any duration of interest to prescribe and monitor match-specific training. For instance, when prescribing a small-sided game aiming to replicate the most intense periods of matches, using Tables 7.1 or 7.2 coaches can predict intensity by inputting intercept, time and slope values into the equation: Intensity = Intercept × $(\text{Time})^{\text{Slope}}$.

Whilst power law has been applied to other football codes (Delaney et al., 2017b; Duthie et al., 2018; Duthie et al., 2017; Lacome et al., 2018), present findings advance the practical application of power law models in team sports by providing novel insights on model prediction typical error as well as the patterns of error as a function of time. Power law models had a typical exercise intensity prediction error of 7.5% and 8.3% for elite and sub-elite rugby respectively, across 5 to 600 second exercise durations. Prediction models typically underestimated shorter (5-10 s) and longer (300-600 s) duration peak exercise intensities and overestimated 20-120 s exercise intensities, by up to ~ 20-25%. The present findings support the use of power law models in team sports to improve match-representative exercise intensity prescription and monitoring for any given exercise duration, using specific game-based methodologies, such as small-sided games. However, practitioners should be aware of prediction model errors when interpreting, prescribing and monitoring match-specific exercise intensities for any given training drill duration.

8.2 Research Progression

Figure 8.1 Research progression



8.3 Practical Applications

The following is a simple list of practical applications and recommendations based upon the findings of the present thesis.

1. Use the right tool for the job. Accelerometers should be used in addition to GPS to quantify, monitor and prescribe player movement in rugby union.
    a. Neither accelerometer nor GPS measures should be used a proxy measure for the other, as they measure different external load constructs (biomechanical and physiological load respectively).
    b. Both speed- and acceleration-based measures should be used to quantify the external load of rugby players.
    c. Use rolling or moving average epoch analysis to more accurately identify and quantify the peak periods of matches and periods thereafter.
    d. Given metabolic power's sensitivity and reliability to quantify movement differences was no better than the other investigated measures, and metabolic power data are hard to prescribe team sport training from, we advise caution with its use.

2. Professional rugby union player movement needs to be monitored across many matches to obtain adequate precision for assessing individuals during intense periods of match-play.
3. Once (2.) has been achieved, peak match intensity data may be used to:
    a. Monitor and contextualise the intensity of training sessions.
    b. Inform training periodization (% training below, at or above match intensity).

c. Inform player match readiness, potentially influencing team selection.
d. Inform player progressions during return to play (% of peak progressions).
e. Inform player transitions between sub-elite and elite levels of competition.

4. Duration- (5 seconds to 10 minutes) and position-specific (i.e. forwards, backs) player movement data derived from wearable technologies and rolling epoch analyses may be used as a reference for training monitoring and prescription to objectively prepare players for the most intense periods of competition. For example, small-sided games may be modified (pitch size, number of players, rules, verbal encouragement) to achieve desired duration- and position-specific physiological and biomechanical external loads whilst simultaneously training technical and tactical skills.
5. Activity profile data post peak periods of competition may inform match-specific high-intensity interval training (HIIT) prescription, programming for both high-intensity periods and for "active recovery" periods between efforts using game-based methodologies such as small-sided games.
6. Improved understanding of player activity profiles post the peak periods of competition may inform match day tactical decisions such as player positional changes, team formation changes and player substitutions or rotations.
7. Rugby coaches may use power law to predict peak speed- and acceleration-based exercise intensities for any duration of interest to prescribe and monitor match-specific training using game-based methods.

a. Practitioners should be aware that there is error associated with exercise intensity prediction models and incorporate this typical error into their interpretation and use of them.

8.3 Limitations

Whilst this series of studies provides many novel and meaningful insights that may aid coaching and performance staff in identifying, quantifying, monitoring and prescribing player peak exercise intensities, there are several limitations that need to be acknowledged.

1. The case study nature of the present study may be considered a limitation and whilst two professional teams of two competitive levels with many repeated measures were included across two seasons, league-wide investigations with opposition analyses is the way forward to better understand collision-based team sport activity profiles.
2. Positional analyses were limited to positional forward and back packs rather than more specific playing positions (e.g., prop, centre, scrum-half) to increase precision of estimates and to first assess if the respective technologies were sensitive enough to quantify broader positional classifications prior to comparing specific positional groupings. Specific playing position groups (e.g. prop, lock, scrum-half) are ideal, provided sample size and number of repeated measures are large enough.
3. Whilst some factors that may influence peak intensities of rugby competition were examined (e.g. time on field, playing position, match-half, level of competition, within-season trends), there are many factors (Table 2.2) that would help to explain fluctuations in exercise intensity during competition.

4. No attempt was made to quantify the frequency and magnitude of collisions during the peak intensity periods of rugby, which would enhance game-based training prescription specificity of the worst-case scenarios of competition.
5. The placement of an accelerometer on the trunk is only an estimate of whole-body accelerations that is far from perfect, although offers a starting point for biomechanical load estimation in the field.
6. Research consensus indicates that metabolic power underestimates energy cost during intermittent team sport movements, underpinning its lack of criterion validity versus portable gas analysers.

8.4 Future Directions

Avenues for future research based upon findings from the present thesis include:

1. Overlaying visual match-analysis with player tracking solutions to synchronise peak and post peak player movement with several contextual factors (e.g. ball in/out of play/possession). Time synchronised performance analyst data tracking player tackles, set piece (e.g. scrums, rucks, mauls, lineouts, penalties etc.) and technical key performance indicators (e.g. passes, meters gained etc.) alongside player movement data during and post peak periods of matches, is the way forward.
    a. The synchronisation of physical, technical and tactical data during the most intense periods of matches and periods thereafter will enhance understanding of player fatigue and pacing strategies, whilst potentially improving tactical decision processes and match representative training prescription and monitoring.

2. Explore the relationships between the most intense passages of play, key technical performance indicators and match outcome (win/loss).
3. Examine the validity, reliability and sensitivity of GPS- and accelerometer-derived measures to quantify team sport movement pre, during and post the most intense periods of competition. New GPS models are constantly emerging or being updated, increasing the necessity for stringent testing of their accuracy and reproducibility.
4. Explore the relationships between a raft of player physical qualities and capacities (e.g. maximal speed, relative strength, aerobic capacity) and their relation, if any, to generating high exercise intensities during match-play.
5. Investigate the influence of sensor location, sensor harnessing and relationships between segmental and whole-body acceleration. For instance, the application of multi-segment accelerometer models to more accurately estimate the mechanical loading of team sport athletes should be examined. Whilst multi-segment models are unlikely to be permitted during competition until further receiver miniaturisation and safety testing occurs, they may be applied during training settings.
6. Investigate nonlinear power or hyperbolic models (e.g. critical power model) that can validly incorporate individual physical/physiological parameters (e.g. metabolic energy contributions) and potentially match contextual factors (e.g. stoppages) in an attempt to improve exercise intensity prediction model goodness of fit, homoscedasticity and prediction error.

8.5 Conclusions

Fluctuations in running intensity are expected during professional rugby competition given its stochastic nature and whole-match averages are not sensitive enough to detect these subtle activity profile fluctuations (Delaney et al., 2016d; Furlan et al., 2015; Jones et al., 2015). Simply assessing the average intensity of competition hides the worst-case scenarios that players will be exposed to in matches. This has ramifications for training prescription, as drills based on whole-match averages will inevitably underprepare athletes for the most intense periods of competition (Delaney et al., 2016d). The intensity of training can be referenced against the peak periods of activity during competition to ensure the players are prepared for the rigours of match-play in a position- and duration-specific manner (Delaney et al., 2016d). This practice increases the likelihood of players thriving and not just surviving during the peak periods of competition due to a reduced relative intensity for the adapted athlete. Coaches should expose their athletes to very intense periods of training in a periodised manner using game-based methodologies such as small-sided games (Delaney et al., 2015) to elicit physiological adaptations (Rampinini et al., 2007b), reduce injury likelihood (Verrall et al., 2005) and improve athlete readiness to perform when confronted with worst-case scenarios during competition. This thesis has provided rugby playing position, match-half and level of competition specific intensities across GPS- and accelerometer-derived metrics for durations of 5 seconds to 10 minutes, to help coaches prescribe and monitor training that is representative of the most intense periods of competition.

This series of studies has clearly established that performance staff and coaches need to “use the right tool for the job”. The use of GPS technology alone underestimates the peak intensities of professional rugby players (namely of forwards as exercise duration increases). Present findings suggest that neither accelerometer nor GPS measures should be used a proxy measure for the other, as they measure different external load constructs. Practitioners should use accelerometers alongside GPS with both speed- and acceleration-based measures to quantify, monitor and prescribe player movement in rugby union and other collision-based team sports.

Findings from this series of studies make it abundantly clear that practitioners should reflect on the strengths and limitations of any technology and its derived measures; understanding its validity, reliability and sensitivity to best interpret and use the data to inform decisions that influence the training process. The poor sensitivity and low reliability of GPS and accelerometer measures of peak intensity imply that rugby players need to be monitored across many matches to obtain adequate precision for assessing individuals.

Accurate identification of the peak intensities of competition using rolling epoch analysis and quantifying subsequent exercise intensity declines has improved limited understanding of rugby player pacing strategies and fatigue, which may inform match-day substitution or rotation decisions, player positional changes and team formations. Similarly, examination of factors that may influence peak player intensities achieved during competition aid broader understanding of the mechanisms underpinning physical "performance". Results of the present thesis underline the need for future research to holistically incorporate physical, contextual, technical and tactical data to begin to unpack the very complex nature of team sport movement and the peak intensities thereof.

Professional rugby coaches may now confidently use power law to predict the peak intensities of competition for any duration of interest. Present findings have advanced the practical application of power law models in team sports by providing novel insights on model prediction typical error as well as the patterns of error as a function of time. This series of studies will enable rugby coaches to more accurately interpret, prescribe and monitor match-specific exercise intensities for any training drill duration of interest. If players are repeatedly exposed to the worst-case scenarios of competition during training in an appropriately periodised manner, the adapted player will thrive and not simply survive when faced with these physically challenging periods during competition.

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